Layer Precision Reduction for Deep Anomaly Detection

Jiawei Yang *
University of Turku
jiaweiyang@ieee.org

Xu Tan
Electric Power Research Institute of Guangdong Power Grid Co., Ltd.
xutan@ieee.org

Matti Kaisti
University of Turku
mkaist@utu.fi

Abstract

Autoencoders (AEs) are widely used in unsupervised Anomaly Detection (AD) due to their ability to model complex data distributions. However, their strong reconstruction capacity, while effective for capturing normal patterns, often enables them to also reconstruct anomalous objects, including both individual and collective anomalies, which reduces detection performance. This limitation is particularly severe for collective anomalies, which are frequently misinterpreted as normal clusters. To address this issue, we propose Layer Precision Reduction (LPR), a novel technique that systematically constrains the numerical precision of weights and biases in neural network layers to strategically reduce the learning capacity of neural networks, such as the reconstruction capacity of AEs. LPR encourages the network to prioritize dominant manifold structures while suppressing the reconstruction of rare or anomalous patterns. While LPR was primarily developed for AE-based detectors (the focus of this paper), it is applicable to any neural network. LPR is applied to 10 deep AD models, including 5 unsupervised AE-based methods, 2 unsupervised non-AE-based methods, 1 semi-supervised method, 1 weakly supervised method, and 1 fully supervised method. Under the oracle setting, LPR improves the average performance of all 10 models across 30 tabular datasets, most notably raising the average Area Under the Receiver Operating Characteristic Curve (AUROC) of the best-performing unsupervised AE-based detector from 72.12% to 83.06%. This exceeds the 77.27% average AUROC achieved by the strongest unsupervised non-AE-based competitor among the remaining 14 detectors. These results reveal a previously unexplored link between layer-level numerical precision and manifold pattern prioritization, demonstrating that LPR serves as a simple yet powerful mechanism for enhancing AD performance while offering broad applicability to diverse neural architectures and potential extensions to tasks beyond AD.

1 Introduction

Anomalies are objects that significantly deviate from other objects in a dataset. Anomaly Detection (AD) is fundamental in a wide range of applications such as medical diagnosis, fraud prevention, network security, and industrial monitoring. AD methods can be categorized as unsupervised, semi-supervised [1], weakly supervised [2], or fully supervised [3]. Given the rarity of labeled anomalies and the high cost of annotation, unsupervised approaches are most commonly used. Over time, both shallow and deep unsupervised models have been developed, each bringing unique advantages across different application domains.

*Corresponding author

40th Conference on Neural Information Processing Systems (NeurIPS 2026).

Among unsupervised deep learning models, Autoencoders (AEs) have become a cornerstone of unsupervised AD due to their strong ability to model complex data distributions through nonlinear dimensionality reduction. This enables AEs to capture essential data manifolds while suppressing noise and irregularities. To further enhance their performance in AD tasks, a wide range of architectural, training, and scoring strategies have been explored. As summarized in Table A1, these efforts target key abilities such as robust learning [4], stability [5], generalizability [6], interpretability [7], and scalability [8]. While these advances significantly improve the modeling of normal data, they overlook a fundamental challenge: *powerful AEs tend to reconstruct not only normal objects but also anomalies, including individual and collective anomalies*. This undermines the core assumption of AE-based AD that anomalies yield higher reconstruction errors. The problem is particularly acute for collective anomalies, which AEs may misinterpret as legitimate clusters.

To address this limitation, we propose Layer Precision Reduction (LPR), a novel technique that adjusts the numerical precision of weights and biases in neural network layers to strategically constrain reconstruction capacity. By enforcing reduced precision of layers, LPR encourages AEs to focus on dominant manifold patterns while suppressing less frequent, potentially anomalous ones. This structural underfitting leads to poor reconstruction of anomalies, thereby improving detection effectiveness. Our empirical focus is tabular AD; extensions to other modalities remain future work. Our key contributions are summarized as follows:

- We uncover a previously unexplored connection between layer-level numerical precision and manifold pattern prioritization in AD. To the best of our knowledge, this is the first work to examine the reconstruction suppression capability of AEs for both normal and anomalous objects in the context of AD.
- We propose LPR, a general enhancement technique for deep anomaly detectors. While primarily designed for unsupervised AE-based models, LPR is also applicable to semi-supervised, weakly supervised, and fully supervised settings. To our knowledge, it is among the very few techniques that improve detection performance across diverse models and supervision levels.
- We conduct comprehensive empirical evaluations involving 24 baseline methods and 30 publicly available real-world datasets.

2 Related work

AD methods can be broadly categorized into Deep Learning (DL)-based and non-DL-based approaches. AEs constitute an important family of DL-based detectors. Existing AE-based detectors improve anomaly detection through architectural modifications and loss design [4, 9]. LPR complements these approaches by controlling parameter precision to shape reconstruction behavior. It is also related to quantization, which has primarily been studied for model compression and computational efficiency [10]. A detailed review is provided in Appendix A.

3 The proposed method

In this section, we introduce LPR. We first present its formulation and then compare it with standard quantization. Its training procedure is provided in Appendix B.2.

3.1 LPR formulation

Let the parameters of a neural network (e.g., an autoencoder) be denoted by $\theta = \{W_\ell, b_\ell\}_{\ell=1}^{L}$, where L is the number of layers, and W_ℓ, b_ℓ are the weights and biases of layer ℓ. To impose limited numerical precision during training, we define a rounding operator for a given layer precision $\Delta_\ell > 0$ as:

$$Q_{\Delta_\ell}(w) = \Delta_\ell \cdot \text{round}\left(\frac{w}{\Delta_\ell}\right), \tag{1}$$

where w is a scalar component of a weight or bias tensor; Q_{Δ_ℓ} acts element-wise on tensors. The set of precision-constrained parameters is then:

$$\tilde{\theta} = \{Q_{\Delta_\ell}(W_\ell), Q_{\Delta_\ell}(b_\ell)\}_{\ell=1}^{L}. \tag{2}$$

The resulting precision-aware network is denoted by:

$$f(x) := f_{\tilde{\theta}}(x). \tag{3}$$

The training loss, such as the reconstruction error in autoencoders, becomes:

$$\mathscr{L}(\tilde{\theta}) = \frac{1}{Nm} \sum_{i=1}^{N} \|f_{\tilde{\theta}}(x_i) - x_i\|_2^2. \tag{4}$$

Here, N is the number of training samples, $x_i \in \mathbb{R}^m$ is the ith sample, and m is the input dimension. At each training step, an optimizer update is followed by parameter projection:

$$g_t = \nabla_{\vartheta} \mathscr{L}(\vartheta)|_{\vartheta=\theta_t}, \qquad \theta_{t+1} = Q_\Delta(\text{OptUpdate}(\theta_t, g_t)), \tag{5}$$

Let $\Delta = (\Delta_1, \ldots, \Delta_L)$ denote the collection of layer-wise precision steps, and let Q_Δ apply Q_{Δ_ℓ} to each layer ℓ. Initial parameter projection is optional in the general LPR procedure. In the experiments reported here, we apply it before the first forward pass, i.e., $\theta_0 = Q_\Delta(\theta_{\text{init}})$. Here, t indexes training steps, θ_{init} denotes the initialized parameters, and OptUpdate denotes an optimizer update. For gradient descent with learning rate η, this becomes $\theta_{t+1} = Q_\Delta(\theta_t - \eta g_t)$. The loss and gradient are evaluated at the current parameters. After each optimizer update, the parameters are projected onto the specified grid and used in the next forward pass. Projection is performed after optimization, without differentiating through the rounding operation or using a straight-through estimator for LPR.

To conveniently tune precision, we set $\Delta_\ell = 10^{-d_\ell}$, where $d_\ell \in \{0, \ldots, d_\ell^{\max}\}$ denotes the number of retained decimal digits. We use a global precision level ($d_\ell = d$) and set $d_\ell^{\max} = 6$, as the highest decimal-place setting in the evaluated candidate range. In the implementation, $d_\ell = 6$ denotes the unrounded float32 baseline, which is approximately equivalent to rounding at six decimal places. Decimal places specify an absolute grid step and are distinct from floating-point significant digits. While $Q_{\Delta_\ell}(\cdot)$ can use any $\Delta_\ell > 0$, we adopt the decimal form for simplicity. Extending to layer-wise precision is left for future work. Selecting d_ℓ without labels is challenging; we discuss heuristics in Section 5.7.

3.2 Difference from standard quantization

LPR differs from standard quantization in both formulation and motivation. Although the two methods can be used jointly, e.g., compressing a model trained with LPR using post-training quantization, their purposes are distinct.

Formulation LPR uses the rounding operator in Eq. (1), where each layer's precision is parameterized as $\Delta_\ell = 10^{-d_\ell}$. In contrast, standard b_{bit}-bit uniform quantization maps a weight w as:

$$Q_{b_{\text{bit}},\Delta}(w) = \Delta \cdot \text{clip}\left(\text{round}\left(\frac{w}{\Delta}\right), -2^{b_{\text{bit}}-1}, 2^{b_{\text{bit}}-1} - 1\right), \tag{6}$$

Here, b_{bit} is the bit width, $\Delta > 0$ is the quantization step size, and $\text{clip}(u, a, c) = \min(\max(u, a), c)$. The quantized parameter set is $\theta_q = \{Q_{b_{\text{bit}},\Delta}(W_\ell), Q_{b_{\text{bit}},\Delta}(b_\ell)\}_{\ell=1}^{L}$, with quantization applied element-wise. The parameters b_{bit} and Δ are typically selected by minimizing:

$$\min_{\theta, b_{\text{bit}}, \Delta} \mathscr{L}_{\text{task}}(\theta_q) + \lambda C(b_{\text{bit}}), \tag{7}$$

where $\mathscr{L}_{\text{task}}$ is the task loss (e.g., classification error), $C(b_{\text{bit}})$ quantifies compression (e.g., memory usage), and λ controls the trade-off.

Motivation The goal of LPR is to improve the *detection performance* during training by adjusting the level of precision, thereby raising the performance upper bound. Conventional quantization is typically motivated by deployment efficiency while retaining task performance; Quantization-Aware Training (QAT) can be performed from scratch or by fine-tuning. These objectives can overlap with regularization effects.

4 Theoretical foundation

This section provides a theoretical perspective on why LPR can improve reconstruction-based AD. We aim to characterize how precision constraints influence the learned solution and may increase the separation between dominant normal patterns and rare or anomalous structures. In particular, we connect LPR to the *manifold pattern prioritization* effect introduced earlier, and provide a formal and intuitive explanation of how this effect arises.

4.1 Precision-constrained hypothesis space

Under LPR, parameters θ are projected onto a discretized space via the rounding operator $Q_{\Delta_\ell}(\cdot)$, yielding $\tilde{\theta}$ and the corresponding model $f_{\tilde{\theta}}$. This induces a precision-constrained hypothesis class:

$$\mathscr{H}_\Delta = \{f_{\tilde{\theta}} : \theta \in \mathbb{R}^P\}. \tag{8}$$

Here P denotes the total number of trainable parameters. As Δ_ℓ increases, the parameter space becomes more coarsely discretized, reducing its resolution. Because different patterns may require different levels of parameter precision, this constraint can affect their reconstruction unequally. When dominant patterns remain representable on a coarse grid while anomalous patterns require finer parameter adjustments, precision reduction biases learning toward the dominant patterns.

4.2 Paired perturbation of reconstruction error

Recall the reconstruction errors:

$$e(x) = \|f_\theta(x) - x\|_2^2, \quad e_\Delta(x) = \|f_{\tilde{\theta}}(x) - x\|_2^2. \tag{9}$$

We assume local Lipschitz continuity with respect to parameters.

Assumption 1 (Parameter Lipschitzness). There exists $L_\theta > 0$ such that:

$$\|f_{\tilde{\theta}}(x) - f_\theta(x)\|_2 \leq L_\theta \|\tilde{\theta} - \theta\|_2. \tag{10}$$

Proposition 1 (Bounded Reconstruction Perturbation). If $B \geq 0$ satisfies $\|f_\theta(x) - x\|_2 \leq B$ and $\|f_{\tilde{\theta}}(x) - x\|_2 \leq B$, then:

$$|e_\Delta(x) - e(x)| \leq 2BL_\theta \|\tilde{\theta} - \theta\|_2. \tag{11}$$

Proof Sketch. Using $\|a\|_2^2 - \|b\|_2^2 = (a-b)^\top (a+b)$ and applying the Cauchy–Schwarz inequality yields the result.

Proposition 1 bounds the change in reconstruction error for a paired parameter perturbation. The selective changes between normal and anomalous samples are considered separately below.

4.3 Reconstruction gap and its amplification mechanism

Let $\mathscr{D}_n$ and $\mathscr{D}_a$ denote the distributions of normal and anomalous data, respectively. The effectiveness of AD depends on the reconstruction gap:

$$G = \mathbb{E}_{x\sim\mathscr{D}_a}[e(x)] - \mathbb{E}_{x\sim\mathscr{D}_n}[e(x)]. \tag{12}$$

LPR aims to increase this gap:

$$\mathbb{E}_{x\sim\mathscr{D}_a}[e_\Delta(x) - e(x)] > \mathbb{E}_{x\sim\mathscr{D}_n}[e_\Delta(x) - e(x)]. \tag{13}$$

Assumption 2 (Representation Asymmetry). Different patterns in the data require different levels of parameter precision to be accurately represented.

In particular, dominant structures can be captured with relatively coarse parameter precision, while other structures require fine-grained parameter values for accurate reconstruction.

This assumption is introduced for explanatory purposes only. LPR does not require anomalies to be low-density or infrequent; more generally, it applies when anomalies correspond to structures that are less stable or more sensitive to precision constraints.

Mechanism interpretation. Under empirical risk minimization, frequently observed normal patterns can dominate aggregate training gradients. If precision constraints affect rare patterns more strongly than dominant patterns, training may preserve dominant structures while underfitting the more precision-sensitive components.

Constructive Example. Consider a two-dimensional input $x = (x_1, x_2) \in \mathbb{R}^2$. Let $x_n \sim \mathscr{D}_n$ and $x_a \sim \mathscr{D}_a$ be defined as:

$$x_n = (z, 0), \quad x_a = (z, r), \tag{14}$$

where $z \sim \mathscr{N}(0,1)$ and $r \neq 0$ denotes the nonzero offset of a component that requires higher parameter precision to reconstruct accurately.

Assume $f_\theta(x) = x$, so that $e(x) = 0$. To illustrate selective reconstruction suppression, consider the reconstruction map:

$$f_{\tilde{\theta}}(x) = (x_1, 0). \tag{15}$$

Then:

$$e_\Delta(x_n) = 0, \quad e_\Delta(x_a) = r^2. \tag{16}$$

Thus:

$$\mathbb{E}_{\mathscr{D}_n}[e_\Delta - e] = 0, \quad \mathbb{E}_{\mathscr{D}_a}[e_\Delta - e] = r^2 > 0, \tag{17}$$

implying the desired inequality.

This construction illustrates how selective suppression increases the reconstruction gap under the specified maps. The nested-subspace model below extends this intuition under explicit assumptions, while the effects of LPR's rounding updates are investigated empirically.

Toy Model Interpretation. Consider a linear autoencoder with decomposition:

$$x = x_{\text{dom}} + x_{\text{rare}}, \quad x_{\text{dom}} \in S_n,\ x_{\text{rare}} \in S_r,\ S_n \perp S_r, \tag{18}$$

where x_{dom} and x_{rare} denote the dominant and rare components, respectively, and S_n and S_r denote their corresponding orthogonal subspaces.

Let $U_L \subset U_H \subseteq \mathbb{R}^m$ be nested subspaces of dimensions k and $k+q$, where $q \geq 1$. Let P_L and P_H denote the orthogonal projections onto U_L and U_H, respectively. Capacity reduction is represented by replacing P_H with P_L. Here, I denotes the identity operator.

Lemma 1 (Selective Reconstruction Error Amplification). Define the increase in reconstruction error by

$$\delta e(x) = \|(I - P_L)x\|_2^2 - \|(I - P_H)x\|_2^2 = \|(P_H - P_L)x\|_2^2. \tag{19}$$

If $S_n \subseteq U_L$, $S_r \subseteq U_H \cap U_L^\perp$, and $x_a = x_{\text{dom}} + x_{\text{rare}}$ with $x_{\text{dom}} \in S_n$ and nonzero $x_{\text{rare}} \in S_r$, then

$$\delta e(x_{\text{dom}}) = 0, \qquad \delta e(x_a) = \|x_{\text{rare}}\|_2^2 > 0. \tag{20}$$

Proof. Since the projections are orthogonal and nested, $(I - P_L)x = (I - P_H)x + (P_H - P_L)x$, and the two terms are orthogonal. The Pythagorean identity gives the first equality. For $x_{\text{dom}} \in U_L$, $(P_H - P_L)x_{\text{dom}} = 0$; for $x_{\text{rare}} \in U_H \cap U_L^\perp$, $(P_H - P_L)x_{\text{rare}} = x_{\text{rare}}$, proving both conclusions.

The lemma describes selective suppression when the retained subspace contains the dominant components and the removed subspace contains the rare components. It gives a conditional linear-model explanation of manifold pattern prioritization. The observed reconstruction behavior is illustrated in Fig. 1 and Table 5.

4.4 Bias–variance perspective

LPR can also be interpreted from a bias–variance perspective under the assumption that model parameters are subject to training randomness, such as data sampling, initialization, or stochastic optimization.

Under this view, $f_{\tilde{\theta}}(x)$ can be regarded as a random function for a fixed input x, and the expectation is taken over the randomness in the training process. The reconstruction error can then be decomposed as:

$$\mathbb{E}\|f_{\tilde{\theta}}(x) - x\|_2^2 = \underbrace{\|\mathbb{E}[f_{\tilde{\theta}}(x)] - x\|_2^2}_{\text{bias}^2} + \underbrace{\mathbb{E}\|f_{\tilde{\theta}}(x) - \mathbb{E}[f_{\tilde{\theta}}(x)]\|_2^2}_{\text{variance}}. \tag{21}$$

Precision reduction changes the attainable parameter grid and can change both bias and variance; the direction of this change depends on the data, architecture, and training dynamics. When fine-grained

patterns are more sensitive to precision constraints, the model may underfit them while retaining coarser structures.

In the context of AD, this bias–variance shift can be beneficial. Full-capacity models may overfit rare or anomalous structures, leading to small reconstruction errors even for anomalies. In contrast, precision-constrained models tend to underfit such low-density patterns, thereby increasing their reconstruction error while preserving dominant normal structures.

4.5 Discussion

LPR constrains parameter precision during training, complementing architectural and loss-based capacity controls. Its effect depends on which structures require fine precision: coarse projection may also underfit legitimate minority normal patterns and increase false positives. Detailed connections to quantization and regularization, and the conditions under which LPR can fail, are in Appendix B.3.

5 Experimental evaluation

Full experimental setup details, including datasets, baselines, evaluation metrics, and implementation, are provided in Appendix B.4. We report AUROC and Area Under the Precision–Recall Curve (AUPRC), and include Post-Training Quantization (PTQ) and QAT comparisons. We report means and Standard Deviations (SDs).

5.1 Selection protocols and interpretation

Test-label oracle denotes candidate selection using the target-test metric. Main-paper oracle results use *seed-wise oracle*: select the best precision separately for each dataset, seed, and metric, then average. *Mean-first oracle* first averages seeds, then selects precision per dataset and metric; it is compared separately in Appendix C.1. Both are label-aware attainable-performance analyses. Constant-score runs are assigned zero in both reported metrics before averaging and precision selection. Excluding constant-score candidates from oracle selection gives identical oracle results. Appendix C.2 compares results with and without the zero penalty. *Fixed precision* uses the same d for every model and dataset. *Leave-One-Dataset-Out (LODO)* selects a shared precision d for all ten models on each held-out dataset by maximizing their average AUROC across the other 29 datasets and ten seeds. Selection uses labels from these source datasets, without using held-out labels.

5.2 Comparison with the first baseline group

The results of applying LPR to the 10 deep AD models from the first baseline group are presented in Table 1.[2] Under test-label oracle settings, LPR improves the average performance of all 10 models. Specifically, it enhances the five unsupervised AE-based models, increasing the average AUROC from 67.42% to 75.29%, and the average AUPRC from 35.22% to 43.02%. The most significant improvement is observed for the U-DRL detector, with an average AUROC gain of 14.22 percentage points and an average AUPRC gain of 13.61 percentage points. The best-performing model among the original unsupervised AE-based baselines is PAE, which achieves an average AUROC of 72.12%. When combined with LPR, its performance increases to 83.06% average AUROC, demonstrating the effectiveness of LPR.

Moreover, LPR also boosts the performance of two unsupervised non-AE-based models, one semi-supervised model, one weakly supervised model, and one fully supervised model. These models experience an average AUROC improvement from 75.90% to 83.22%, and an average AUPRC improvement from 51.23% to 58.43%. These oracle findings demonstrate the potential of LPR across architectures and supervision levels, while the results under fixed-precision (e.g., $d = 5$) and leave-one-dataset-out (LODO) selection highlight the importance of precision selection for realizing these gains in practice. Further exploration of LPR's impact on additional models remains a promising direction for future work.

[2] Baseline method names and abbreviations follow the definitions in their respective original papers; the corresponding references are listed in Table A5.

Table 1: AUROC and AUPRC (%): mean ± SD over 30 datasets and ten seeds. Fixed-precision and LODO columns are additional analyses. Sup. denotes training supervision: U, unsupervised; S, semi-supervised; W, weakly supervised; F, fully supervised; Oracle uses test labels to select precision. Both reported metrics use the constant-score zero-penalty convention.

(a) AUROC

Detector	Sup.	Original	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$	LODO	Oracle
AE	U	65.00 ±21.07	62.45 ±23.41	61.94 ±23.09	61.79 ±23.48	65.05 ±21.01	64.99 ±21.10	65.01 ±21.08	64.99 ±21.07	64.99 ±21.08	72.15 ±18.99
MCM	U	70.76 ±20.91	62.26 ±23.25	68.91 ±23.44	66.44 ±21.26	69.12 ±20.59	69.33 ±21.55	70.20 ±20.98	70.76 ±20.91	69.93 ±21.08	77.89 ±18.28
DTE	U	65.42 ±22.12	0.00 ±0.00	0.00 ±0.00	48.79 ±23.77	49.33 ±23.62	63.82 ±23.04	65.67 ±21.27	65.42 ±22.12	65.16 ±22.00	75.92 ±15.63
VAE	U	64.60 ±18.72	62.42 ±23.41	60.33 ±18.64	60.08 ±18.99	64.33 ±18.64	64.60 ±18.72	64.60 ±18.72	64.60 ±18.72	64.60 ±18.72	71.67 ±18.17
β-VAE	U	64.62 ±18.64	62.42 ±23.41	60.33 ±18.64	60.08 ±18.99	64.31 ±18.60	64.62 ±18.64	64.62 ±18.64	64.62 ±18.64	64.62 ±18.64	71.69 ±18.16
PAE	U	72.12 ±22.33	63.58 ±23.48	60.98 ±23.20	61.06 ±23.28	69.58 ±24.20	71.81 ±22.27	72.30 ±21.60	72.12 ±22.33	71.27 ±22.72	83.06 ±14.16
U-DRL	U	64.39 ±21.35	0.00 ±0.00	65.98 ±23.69	65.62 ±20.87	65.21 ±20.95	64.83 ±21.16	64.55 ±21.24	64.39 ±21.35	64.35 ±21.14	78.61 ±17.30
S-DRL	S	76.98 ±19.17	0.00 ±0.00	64.38 ±24.32	73.15 ±18.61	76.16 ±17.79	76.96 ±19.24	77.02 ±19.31	76.98 ±19.17	76.89 ±19.38	82.33 ±16.14
FEAWAD	W	82.84 ±15.58	0.00 ±0.00	46.31 ±27.11	48.85 ±25.92	83.46 ±16.38	82.69 ±16.13	82.73 ±16.00	82.84 ±15.58	82.73 ±15.98	87.39 ±12.15
MLP	F	89.87 ±17.35	0.00 ±0.00	45.56 ±26.53	48.74 ±25.03	88.90 ±18.78	89.46 ±17.86	90.03 ±16.72	89.87 ±17.35	89.86 ±17.36	91.86 ±13.68
Average	–	71.66	31.31	53.47	59.46	69.54	71.31	71.67	71.66	71.44	79.26

(b) AUPRC

Detector	Sup.	Original	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$	LODO	Oracle
AE	U	35.28 ±28.78	32.28 ±29.29	31.07 ±27.87	31.19 ±28.06	35.06 ±28.66	35.27 ±28.74	35.29 ±28.79	35.28 ±28.78	35.28 ±28.77	40.34 ±29.10
MCM	U	36.11 ±27.43	32.67 ±29.31	40.59 ±31.88	31.23 ±25.98	34.01 ±26.25	34.50 ±27.40	35.95 ±28.45	36.11 ±27.43	35.36 ±27.87	47.01 ±29.82
DTE	U	37.61 ±28.78	0.00 ±0.00	0.00 ±0.00	23.56 ±24.49	24.29 ±24.70	36.55 ±28.29	37.31 ±28.64	37.61 ±28.78	37.21 ±28.66	45.28 ±29.98
VAE	U	33.33 ±27.91	32.13 ±29.27	27.09 ±27.43	27.31 ±27.59	32.08 ±26.72	33.34 ±27.92	33.33 ±27.91	33.33 ±27.91	33.33 ±27.91	39.13 ±29.41
β-VAE	U	33.38 ±27.93	32.13 ±29.27	27.09 ±27.43	27.31 ±27.59	32.07 ±26.70	33.39 ±27.94	33.38 ±27.94	33.38 ±27.93	33.38 ±27.94	39.17 ±29.42
PAE	U	37.98 ±29.31	32.74 ±29.18	30.76 ±27.97	30.67 ±28.03	36.73 ±29.25	37.12 ±29.42	37.38 ±28.56	37.98 ±29.31	37.31 ±29.00	49.47 ±31.02
U-DRL	U	32.82 ±26.55	0.00 ±0.00	37.19 ±29.98	32.49 ±25.76	33.16 ±26.40	32.36 ±25.80	32.01 ±25.27	32.82 ±26.55	32.33 ±26.19	46.43 ±30.61
S-DRL	S	48.99 ±31.34	0.00 ±0.00	34.54 ±29.57	41.00 ±31.40	44.81 ±31.09	49.23 ±31.30	49.98 ±31.38	48.99 ±31.34	49.35 ±31.01	55.40 ±31.67
FEAWAD	W	62.46 ±25.49	0.00 ±0.00	22.37 ±24.99	23.59 ±24.16	64.09 ±26.42	62.20 ±25.89	62.38 ±25.80	62.46 ±25.49	62.50 ±25.81	68.38 ±25.11
MLP	F	74.25 ±31.27	0.00 ±0.00	21.37 ±24.76	24.28 ±26.04	72.84 ±32.17	73.94 ±31.47	74.27 ±31.21	74.25 ±31.27	74.26 ±31.24	76.68 ±29.48
Average	–	43.22	16.20	27.21	29.26	40.91	42.79	43.13	43.22	43.03	50.73

5.3 Comparison with the second baseline group

PAE combined with LPR (denoted as PAE*) is compared against 14 baseline methods, as shown in Table 2. The original PAE achieves an average AUROC of 72.12%, which is lower than several existing detectors such as IForest, KNN, LDGOD, and DIF, all of which exceed 75% in average AUROC. Under the oracle selection of LPR precision, PAE* achieves higher average AUROC and AUPRC than these methods. Specifically, PAE* outperforms the best existing baseline, KNN, with an average AUROC of 83.06% compared to 77.27%, and an average AUPRC of 49.47% versus 42.12%.

5.4 Comparison with regularization and quantization methods

Table 3 compares LPR with regularization and quantization methods. Under oracle selection, LPR improves AUROC and AUPRC over its AE baseline by 7.15 and 5.06 percentage points, respectively. LPR has the highest AUROC and AUPRC among the tested alternatives. Note that LPR and signed 8-bit integer (INT8) QAT impose different numerical constraints: INT8 bit width and decimal precision

Table 2: Comparison with other baselines (%). PAE* uses oracle selection of LPR precision.

	AUROC		AUPRC	
Method	Mean	SD	Mean	SD
LOF	69.55	17.31	28.95	22.10
OCSVM	68.53	21.56	39.90	30.16
IForest	75.35	17.24	40.89	31.31
KNN	77.27	20.20	42.12	25.85
ECOD	71.84	17.24	37.30	27.56
MGBOD	67.99	24.30	27.99	26.86
ODHD	26.23	19.72	13.67	16.32
LDGOD	77.02	18.37	39.79	25.35
ICL	51.27	15.54	20.45	19.06
DeepSVDD	58.15	10.78	22.01	18.53
DIF	75.77	18.87	40.16	29.05
SLAD	67.55	20.97	32.17	23.49
RCA	69.13	18.18	36.52	27.65
NeuTraL	67.82	16.63	27.91	22.42
PAE*	83.06	14.16	49.47	31.02

Table 3: Regularization and quantization comparison (%). SD is computed across 30 datasets and ten random seeds. Methods with multiple hyperparameter candidates (Dropout, weight decay, Noise, and LPR) use seed-wise oracle selection.

	AUROC		AUPRC	
Method	Mean	SD	Mean	SD
AE	65.00	21.07	35.28	28.78
Dropout	68.40	21.17	39.71	32.24
Weight decay	65.00	21.07	35.29	28.78
Noise	66.23	21.14	36.60	29.37
PTQ	65.00	21.07	35.29	28.78
QAT	64.85	21.06	34.95	28.75
LPR	72.15	18.99	40.34	29.10

are not directly equivalent. The QAT baseline uses a range-dependent quantization step and quantizes hidden activations, whereas LPR rounds only parameters to a fixed decimal grid. Implementation details are provided in Appendix C.3. Per-dataset results are provided in Tables A50–A55.

5.5 Comparison with AE components

To compare layer precision with other AE components, we evaluate 20 configurations varying layers, the presence of Rectified Linear Units (ReLU) and bias terms, and reconstruction loss and anomaly scoring functions. The latter use Mean Absolute Error (L1), Mean Squared Error (L2), or Smooth L1 (SL1). Table 4 summarizes performance with and without LPR; per-dataset results are provided in Tables A28–A47.

Without LPR, average AUROC ranges from 64.66% to 69.56%, and average AUPRC from 34.05% to 40.70%. Under oracle precision selection, LPR improves AUROC and AUPRC by an average of 5.59 and 4.51 percentage points, respectively, across these configurations.

5.6 Analysis of LPR's mechanism

To better understand the mechanism behind LPR, we visualized the latent features learned by AEs with and without LPR. As shown in Fig. 1 (left), the original AE captures both cluster structures and their relative spatial positions. In contrast, when LPR is applied (i.e., with reduced layer precision), the AE primarily preserves cluster memberships while discarding finer-grained spatial relationships. Notably, while the original AE identifies all three clusters, including a small one, the AE with LPR focuses only on the two dominant clusters, effectively suppressing minor patterns. This suggests that LPR encourages the network to emphasize major manifold structures while downplaying less informative details. Such behavior can increase reconstruction errors more for anomalies than for normal samples, thereby improving score separability. Consequently, as illustrated in Fig. 1 (right), LPR enhances the AE's ability to detect collective anomalies.

Table 5 shows that LPR increases the mean score of anomalous samples by a larger amount than that of normal samples, widening the anomaly–normal mean score gap from 3.60 to 10.72 for AE and from 14.62 to 23.18 for PAE. This differential increase supports the proposed mechanism of selective reconstruction suppression.

5.7 LPR's parameter analysis

The best precision varies across models and datasets. Across 3,000 runs (10 detectors $\times$ 30 datasets $\times$ 10 seeds), $d = 0, 1, 2, 3, 4, 5, 6$ achieves the highest AUROC in 20.03%, 12.03%, 9.43%, 19.70%, 15.37%, 11.70%, and 11.73% of runs, respectively. Ties are resolved by choosing the smaller d. Detailed results are provided in Tables A18–A27.

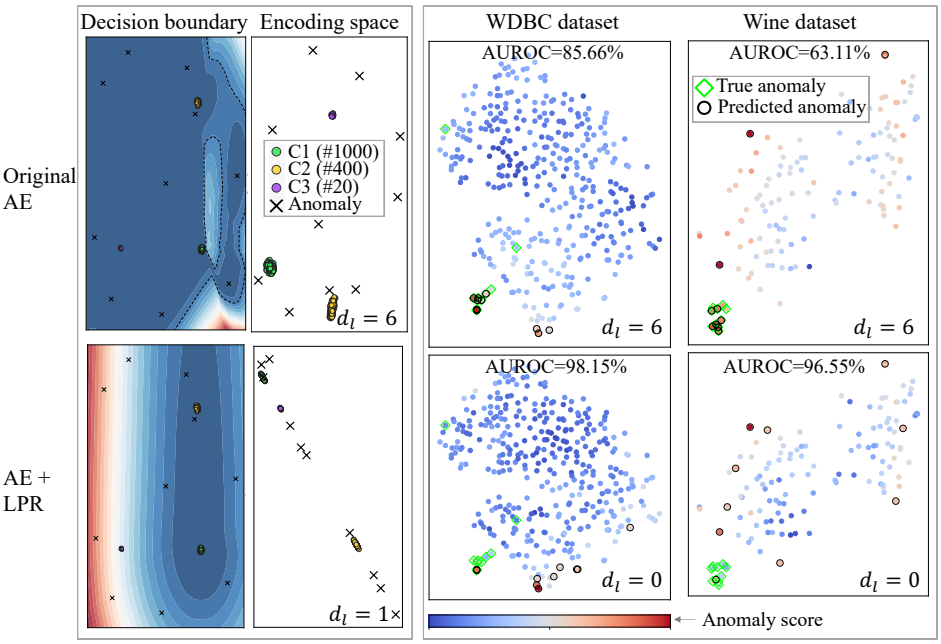


Figure 1: Comparison of AEs without (top row) and with (bottom row) LPR on a synthetic dataset (left) and real-world datasets (right). **Left:** A two-dimensional (2D) synthetic dataset comprising three clusters (C1, C2, and C3) with 1,000, 400, and 20 points, respectively, plus 10 anomalous points, is used with a nine-layer AE with [128, 64, 32, 16, 8, 16, 32, 64, 128] units and ReLU activations. Without LPR, the AE captures both cluster structure and relative positioning. With LPR ($d_\ell = 1$), only dominant clusters are preserved, while minor patterns (e.g., small clusters or isolated points) are poorly reconstructed. **Right:** On real-world datasets (WDBC and Wine), LPR improves AD by prioritizing major patterns and suppressing less relevant information in the reconstruction.

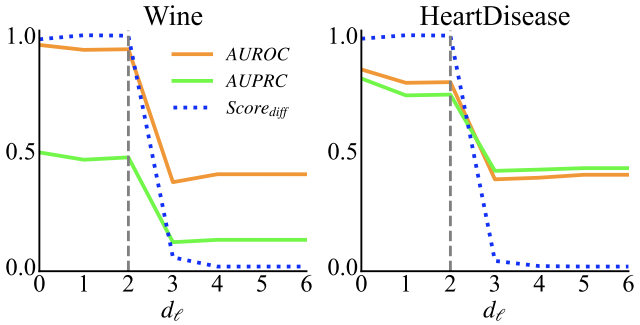


Figure 2: A potential approach for selecting the optimal d_ℓ is to identify the turning point (indicated by the grey dashed line) in the change of mean anomaly scores, relative to those produced by the original model (i.e., with $d_\ell = 6$). **Left:** Wine dataset. **Right:** HeartDisease dataset. `Scorediff` denotes the plotted change in mean anomaly score relative to the original model.

The average AUROC across all ten detectors is 31.31%, 53.47%, 59.46%, 69.54%, 71.31%, 71.67%, and 71.66% for fixed $d = 0, 1, 2, 3, 4, 5, 6$, respectively (Table 1). The highest average is achieved at $d = 5$, with little difference from $d = 6$.

LODO selects a shared precision for all ten models by maximizing their average AUROC on the other 29 datasets, then applies it to both AUROC and AUPRC on the held-out dataset. Its average AUROC and AUPRC are 71.44% and 43.03%, respectively. Per-dataset results are provided in Appendix C.4; results without the zero penalty are reported in Table A9.

Precision can also be explored through changes in anomaly scores as d_ℓ varies. A turning point in the score curve may indicate a useful precision level, as illustrated in Fig. 2. In this exploratory analysis,

Table 4: Comparison of AE components (%), averaged over 30 datasets. Configurations are listed as Layers/ReLU/Bias/Loss/Scoring, where Y and N denote enabled and disabled, respectively. LPR uses oracle precision selection. $\Delta\mu$ and $\Delta\sigma$ denote LPR minus Original mean and SD, respectively; $\Delta\sigma$ is not the SD of a paired gain.

Configuration	AUROC				AUPRC				Δ_{AUROC}		Δ_{AUPRC}	
	Original		LPR		Original		LPR		LPR − Original			
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$
2/Y/Y/L1/L1	68.87	20.27	74.20	18.47	38.91	31.85	43.46	31.87	5.33	-1.80	4.55	0.02
3/Y/Y/L1/L1	69.56	20.21	73.91	18.46	38.28	30.14	42.22	30.41	4.35	-1.75	3.94	0.28
4/Y/Y/L1/L1	67.91	20.53	72.17	19.11	36.26	30.23	39.69	30.77	4.26	-1.42	3.43	0.54
5/Y/Y/L1/L1	67.87	20.99	71.86	19.83	36.24	30.17	39.81	30.62	3.99	-1.17	3.57	0.45
2/Y/Y/L2/L2	64.99	21.07	72.15	18.99	35.28	28.78	40.34	29.10	7.16	-2.08	5.06	0.32
3/Y/Y/L2/L2	65.97	20.76	71.70	18.81	35.23	27.87	39.36	28.26	5.73	-1.95	4.13	0.39
4/Y/Y/L2/L2	64.66	21.68	70.47	20.05	34.05	28.31	38.17	28.79	5.81	-1.63	4.12	0.47
5/Y/Y/L2/L2	65.24	21.16	70.60	20.07	34.19	28.22	38.03	28.52	5.36	-1.09	3.85	0.30
2/Y/Y/SL1/SL1	65.00	21.07	72.22	19.00	35.28	28.77	40.41	29.10	7.22	-2.07	5.13	0.33
3/Y/Y/SL1/SL1	66.00	20.80	71.72	18.84	35.30	27.91	39.41	28.26	5.73	-1.95	4.10	0.35
4/Y/Y/SL1/SL1	64.66	21.68	70.50	20.04	34.05	28.32	38.21	28.80	5.84	-1.64	4.17	0.48
5/Y/Y/SL1/SL1	65.25	21.16	70.55	20.10	34.19	28.24	37.98	28.55	5.29	-1.06	3.79	0.30
3/Y/Y/L2/L1	69.53	20.80	75.63	18.22	40.58	31.88	45.73	32.79	6.10	-2.58	5.15	0.92
3/Y/N/L2/L1	67.14	22.11	71.66	21.27	39.89	32.34	44.00	33.39	4.53	-0.84	4.11	1.05
3/N/Y/L2/L1	68.91	20.69	75.73	17.95	40.24	31.66	45.88	32.79	6.82	-2.74	5.64	1.13
3/N/N/L2/L1	66.83	21.46	72.35	20.55	39.14	32.19	44.34	33.27	5.52	-0.91	5.20	1.08
3/Y/Y/L1/L2	68.82	21.84	75.24	18.38	40.70	32.14	45.72	32.39	6.42	-3.46	5.02	0.25
3/Y/N/L1/L2	68.31	20.87	72.43	20.29	39.58	31.55	43.90	32.42	4.13	-0.58	4.32	0.86
3/N/Y/L1/L2	68.53	22.02	75.65	18.36	40.35	31.81	45.99	32.27	7.12	-3.65	5.63	0.46
3/N/N/L1/L2	68.07	20.66	73.17	19.86	39.10	31.51	44.32	32.32	5.10	-0.80	5.22	0.81

Table 5: Anomaly-score statistics averaged over 30 datasets. Seeds are listed in Table A49. For AE, both Original and LPR use the same seed, selected for the largest oracle AUROC gain among ten seeds on each dataset. *n* and *o* denote normal and anomalous samples; Mean and SD denote the score mean and standard deviation. SD is computed separately for normal and anomalous sample scores, then averaged over datasets. Superscripts (o,n) and (Ori,LPR) denote anomaly-minus-normal and LPR-minus-Original differences, respectively.

	Original				LPR				Difference			
Detector	Mean_n	SD_n	Mean_o	SD_o	Mean_n	SD_n	Mean_o	SD_o	$\text{Mean}^{o,n}_{\text{Ori}}$	$\text{Mean}^{o,n}_{\text{LPR}}$	$\text{Mean}_n^{\text{Ori,LPR}}$	$\text{Mean}_o^{\text{Ori,LPR}}$
AE	19.70	8.97	23.30	12.22	22.70	9.34	33.42	12.94	3.60	10.72	3.01	10.12
PAE	15.75	9.99	30.37	14.94	16.75	9.51	39.93	14.15	14.62	23.18	1.00	9.56

the heuristic identified useful precision on 13 of 30 datasets. Visualizing anomaly scores in the input or latent space can further illustrate how precision affects separation; dimensionality reduction or sampling can support such inspection for high-dimensional or large datasets. Developing a reliable precision-selection rule without labels remains a direction for future work.

6 Conclusion

We propose LPR, a simple training-time technique that reduces layer precision to suppress anomaly reconstruction in AE-based AD. By constraining parameter precision, LPR controls model capacity and promotes dominant structures while underfitting precision-sensitive patterns, improving detection performance across diverse models and supervision settings. These findings reveal, for the first time, a link between the numerical precision of neural network parameters and the prioritization of dominant patterns during learning, suggesting a useful way to improve AD. LPR is a plug-and-play training technique that operates directly on trainable parameters without changing model architectures or loss functions. The results suggest that parameter precision offers an additional way to shape what neural networks learn. Its effectiveness depends on how precision constraints interact with the target task and data distribution. Oracle precision selection reveals substantial potential for improving AD, while efficiently selecting the precision level without labels remains a challenge.

Acknowledgements and Disclosures

We thank Christian Igel and Jonathan Voersaa Wenshøj for helpful discussions and valuable comments.

This project has received funding from the European Union's Horizon Europe research and innovation programme under Marie Skłodowska-Curie grant agreement No. 101126611.

The authors declare no competing interests.

References

[1] H. Ye, H. Zhao, W. Fan, M. Zhou, D. Guo, and Y. Chang, "Drl: Decomposed representation learning for tabular anomaly detection," in *The Thirteenth International Conference on Learning Representations*, 2025.

[2] Y. Zhou, X. Song, Y. Zhang, F. Liu, C. Zhu, and L. Liu, "Feature encoding with autoencoders for weakly supervised anomaly detection," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 6, pp. 2454–2465, 2021.

[3] C. L. Castro and A. P. Braga, "Novel cost-sensitive approach to improve the multilayer perceptron performance on imbalanced data," *IEEE transactions on neural networks and learning systems*, vol. 24, no. 6, pp. 888–899, 2013.

[4] D. Gong, L. Liu, V. Le, B. Saha, M. R. Mansour, S. Venkatesh, and A. v. d. Hengel, "Memorizing normality to detect anomaly: Memory-augmented deep autoencoder for unsupervised anomaly detection," in *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 1705–1714, 2019.

[5] S. Sanami and A. G. Aghdam, "Aero-engines anomaly detection using an unsupervised fisher autoencoder," in *2024 IEEE 63rd Conference on Decision and Control (CDC)*, pp. 553–558, IEEE, 2024.

[6] Y. Liu, H. Wang, Z. Wang, X. Zhu, J. Liu, P. Sun, R. Tang, J. Du, V. C. Leung, and L. Song, "Crcl: Causal representation consistency learning for anomaly detection in surveillance videos," *IEEE Transactions on Image Processing*, 2025.

[7] S. Gautam, A. Boubekki, S. Hansen, S. Salahuddin, R. Jenssen, M. Höhne, and M. Kampffmeyer, "Protovae: A trustworthy self-explainable prototypical variational model," *Advances in Neural Information Processing Systems*, vol. 35, pp. 17940–17952, 2022.

[8] W. Shang, J. Qiu, H. Shi, S. Wang, L. Ding, and Y. Xiao, "An efficient anomaly detection method for industrial control systems: deep convolutional autoencoding transformer network," *International Journal of Intelligent Systems*, vol. 2024, no. 1, p. 5459452, 2024.

[9] X. Tan, J. Yang, J. Chen, S. Rahardja, and S. Rahardja, "Mss-pae: Saving autoencoder-based outlier detection from unexpected reconstruction," *Pattern Recognition*, vol. 163, p. 111467, 2025.

[10] A. Gholami, S. Kim, Z. Dong, Z. Yao, M. W. Mahoney, and K. Keutzer, "A survey of quantization methods for efficient neural network inference," in *Low-power computer vision*, pp. 291–326, Chapman and Hall/CRC, 2022.

[11] V. Livernoche, V. Jain, Y. Hezaveh, and S. Ravanbakhsh, "On diffusion modeling for anomaly detection," in *The Twelfth International Conference on Learning Representations*, 2024.

[12] J. Ye, Z. Tan, Y. Hu, X. Yang, G. Cheng, and K. Huang, "Disentangling tabular data towards better one-class anomaly detection," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 39, pp. 13061–13068, 2025.

[13] J. Yin, Y. Qiao, Z. Zhou, X. Wang, and J. Yang, "Mcm: Masked cell modeling for anomaly detection in tabular data," in *The Twelfth International Conference on Learning Representations*, 2024.

[14] J. Yang, S. Rahardja, and P. Fränti, "Smoothing outlier scores is all you need to improve outlier detectors," *IEEE Transactions on Knowledge and Data Engineering*, vol. 36, no. 11, pp. 7044–7057, 2023.

[15] J. Yang, Y. Chen, and S. Rahardja, "Neighborhood representative for improving outlier detectors," *Information Sciences*, vol. 625, pp. 192–205, 2023.

[16] S. Li, Y. Lu, S. Jiu, H. Huang, G. Yang, and J. Yu, "Prototype-oriented hypergraph representation learning for anomaly detection in tabular data," *Information Processing & Management*, vol. 62, no. 1, p. 103877, 2025.

[17] W. Dai, K. Hwang, and J. Fan, "Unsupervised anomaly detection for tabular data using deep noise evaluation," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 39, pp. 11553–11562, 2025.

[18] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," in *International Conference on Learning Representations (ICLR)*, 2014.

[19] C. P. Burgess, I. Higgins, A. Pal, L. Matthey, N. Watters, G. Desjardins, and A. Lerchner, "Understanding disentangling in *beta*-vae," *arXiv preprint arXiv:1804.03599*, 2018.

[20] X. Li, K. Xie, X. Wang, G. Xie, K. Li, J. Cao, D. Zhang, and J. Wen, "A light-weight and robust tensor convolutional autoencoder for anomaly detection," *IEEE Transactions on Knowledge and Data Engineering*, vol. 36, no. 9, pp. 4346–4360, 2023.

[21] M. S. Battikh and A. A. Lenskiy, "Latent-insensitive autoencoders for anomaly detection," *Mathematics*, vol. 10, no. 1, p. 112, 2021.

[22] D. L. Aguilar, M. A. Medina-Perez, O. Loyola-Gonzalez, K.-K. R. Choo, and E. Bucheli-Susarrey, "Towards an interpretable autoencoder: A decision-tree-based autoencoder and its application in anomaly detection," *IEEE transactions on dependable and secure computing*, vol. 20, no. 2, pp. 1048–1059, 2022.

[23] J. Wu, S. Chen, Q. Zhao, R. Sergazinov, C. Li, S. Liu, C. Zhao, T. Xie, H. Guo, C. Ji, *et al.*, "Switchtab: Switched autoencoders are effective tabular learners," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 38, pp. 15924–15933, 2024.

[24] X. Wang, Y. Du, S. Lin, P. Cui, Y. Shen, and Y. Yang, "advae: A self-adversarial variational autoencoder with gaussian anomaly prior knowledge for anomaly detection," *Knowledge-Based Systems*, vol. 190, p. 105187, 2020.

[25] J. Yang, J. Xie, G. Zhu, S. Kwong, and Y.-Q. Shi, "An effective method for detecting double jpeg compression with the same quantization matrix," *IEEE Transactions on Information Forensics and Security*, vol. 9, no. 11, pp. 1933–1942, 2014.

[26] F. Mentzer, D. Minnen, E. Agustsson, and M. Tschannen, "Finite scalar quantization: Vq-vae made simple," in *The Twelfth International Conference on Learning Representations*, 2024.

[27] D. G. Harris, T. Pensyl, A. Srinivasan, and K. Trinh, "Dependent randomized rounding for clustering and partition systems with knapsack constraints," *Journal of Machine Learning Research*, vol. 23, no. 81, pp. 1–41, 2022.

[28] J. Kim, S. Yoon, T. Lee, J. C. Lee, K. E. Jeon, and J. H. Ko, "Truncquant: Truncation-ready quantization for dnns with flexible weight bit precision," *arXiv preprint arXiv:2506.11431*, 2025.

[29] C. Zhou and R. C. Paffenroth, "Anomaly detection with robust deep autoencoders," in *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining*, pp. 665–674, 2017.

[30] C. Pablos, Á. G. Andrade, and G. Galaviz, "Modulation-agnostic spectrum sensing based on anomaly detection for cognitive radio," *ICT Express*, vol. 9, no. 3, pp. 398–402, 2023.

[31] B. Zong, Q. Song, M. R. Min, W. Cheng, C. Lumezanu, D. Cho, and H. Chen, "Deep autoencoding gaussian mixture model for unsupervised anomaly detection," in *International conference on learning representations*, 2018.

[32] M. Yang, F. Liu, Z. Chen, X. Shen, J. Hao, and J. Wang, "Causalvae: Structured causal disentanglement in variational autoencoder," *arXiv preprint arXiv:2004.08697*, 2020.

[33] S. A. Najafi, M. H. Asemani, and P. Setoodeh, "Attention and autoencoder hybrid model for unsupervised online anomaly detection," *arXiv preprint arXiv:2401.03322*, 2024.

[34] X. Liu, S. Zhu, F. Yang, and S. Liang, "Research on unsupervised anomaly data detection method based on improved automatic encoder and gaussian mixture model," *Journal of Cloud Computing*, vol. 11, no. 1, p. 58, 2022.

[35] N. Ehsani, F. Aminifar, and H. Mohsenian-Rad, "Convolutional autoencoder anomaly detection and classification based on distribution pmu measurements," *IET generation, transmission & distribution*, vol. 16, no. 14, pp. 2816–2828, 2022.

[36] J. Zhu, F. Deng, J. Zhao, and J. Chen, "Adaptive aggregation-distillation autoencoder for unsupervised anomaly detection," *Pattern Recognition*, vol. 131, p. 108897, 2022.

[37] A. J. Hashim, M. Balafar, J. Tanha, and A. Baradarani, "Aevae: adaptive evolutionary autoencoder for anomaly detection in time series," *IEEE Transactions on Neural Networks and Learning Systems*, 2025.

[38] F. Wang, C. Liu, L. Shi, and H. Pang, "Minimaxad: A lightweight autoencoder for feature-rich anomaly detection," *Computers in Industry*, vol. 171, p. 104315, 2025.

[39] D. P. Kingma, M. Welling, *et al.*, "An introduction to variational autoencoders," *Foundations and Trends® in Machine Learning*, vol. 12, no. 4, pp. 307–392, 2019.

[40] A. Ng *et al.*, "Sparse autoencoder," *CS294A Lecture notes*, vol. 72, no. 2011, pp. 1–19, 2011.

[41] M. Pietroń, D. Żurek, K. Faber, and R. Corizzo, "Towards efficient deep autoencoders for multivariate time series anomaly detection," in *International Conference on Computational Science*, pp. 461–469, Springer, 2024.

[42] B. Sharmila and R. Nagapadma, "Quantized autoencoder (qae) intrusion detection system for anomaly detection in resource-constrained iot devices using rt-iot2022 dataset," *Cybersecurity*, vol. 6, no. 1, p. 41, 2023.

[43] X. Li and S. Ji, "Defense-vae: A fast and accurate defense against adversarial attacks," in *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pp. 191–207, Springer, 2019.

[44] P. Vincent, H. Larochelle, Y. Bengio, and P.-A. Manzagol, "Extracting and composing robust features with denoising autoencoders," in *Proceedings of the 25th international conference on Machine learning*, pp. 1096–1103, 2008.

[45] J. An and S. Cho, "Variational autoencoder based anomaly detection using reconstruction probability," tech. rep., SNU Data Mining Center, 2015.

[46] B. X. Yong and A. Brintrup, "Bayesian autoencoders with uncertainty quantification: Towards trustworthy anomaly detection," *Expert Systems with Applications*, vol. 209, p. 118196, 2022.

[47] A. Grover and S. Ermon, "Uncertainty autoencoders: Learning compressed representations via variational information maximization," in *The 22nd international conference on artificial intelligence and statistics*, pp. 2514–2524, PMLR, 2019.

[48] P. Wiessner, G. Bezirganyan, S. Sellami, R. Chbeir, and H.-J. Bungartz, "Uncertainty-aware time series anomaly detection," *Future internet*, vol. 16, no. 11, p. 403, 2024.

[49] S. Bhatia, A. Jain, S. Srivastava, K. Kawaguchi, and B. Hooi, "Memstream: Memory-based streaming anomaly detection," in *Proceedings of the ACM Web Conference 2022*, pp. 610–621, 2022.

[50] O. Weng, "Neural network quantization for efficient inference: A survey," *arXiv preprint arXiv:2112.06126*, 2021.

[51] B. Jacob, S. Kligys, B. Chen, M. Zhu, M. Tang, A. Howard, H. Adam, and D. Kalenichenko, "Quantization and training of neural networks for efficient integer-arithmetic-only inference," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2704–2713, 2018.

[52] I. Loshchilov and F. Hutter, "Decoupled weight decay regularization," *arXiv preprint arXiv:1711.05101*, 2017.

[53] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, P.-A. Manzagol, and L. Bottou, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion.," *Journal of machine learning research*, vol. 11, no. 12, 2010.

[54] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[55] G. Campos, A. Zimek, J. Sander, R. Campello, B. Micenkova, E. Schubert, I. Assent, and M. Houle, "On the evaluation of unsupervised outlier detection: measures, datasets, and an empirical study," *Data Mining and Knowledge Discovery*, vol. 30, no. 4, pp. 891–927, 2016.

[56] D. Dua and C. Graff, "Uci machine learning repository," *School of Information and Computer Science, University of California*, 2019.

[57] M. M. Breunig, H.-P. Kriegel, R. T. Ng, and J. Sander, "Lof: identifying density-based local outliers," in *Proceedings of the 2000 ACM SIGMOD international conference on Management of data*, pp. 93–104, 2000.

[58] B. Schölkopf, J. C. Platt, J. Shawe-Taylor, A. J. Smola, and R. C. Williamson, "Estimating the support of a high-dimensional distribution," *Neural computation*, vol. 13, no. 7, pp. 1443–1471, 2001.

[59] F. T. Liu, K. M. Ting, and Z.-H. Zhou, "Isolation forest," in *2008 eighth ieee international conference on data mining*, pp. 413–422, IEEE, 2008.

[60] E. M. Knox and R. T. Ng, "Algorithms for mining distancebased outliers in large datasets," in *Proceedings of the international conference on very large data bases*, pp. 392–403, Citeseer, 1998.

[61] Z. Li, Y. Zhao, X. Hu, N. Botta, C. Ionescu, and G. Chen, "Ecod: Unsupervised outlier detection using empirical cumulative distribution functions," *IEEE Transactions on Knowledge and Data Engineering*, 2022.

[62] C. Gao, X. Tan, J. Zhou, W. Ding, and W. Pedrycz, "Fuzzy granule density-based outlier detection with multi-scale granular balls," *IEEE Transactions on Knowledge and Data Engineering*, 2025.

[63] R. Wang, S. H. Moon, X. S. Hu, X. Jiao, and D. Reis, "A computing-in-memory-based one-class hyperdimensional computing model for outlier detection," *IEEE Transactions on Computers*, vol. 73, no. 6, pp. 1559–1574, 2024.

[64] H. Liu, S. Zhang, Z. Wu, and X. Li, "Outlier detection using local density and global structure," *Pattern Recognition*, vol. 157, p. 110947, 2025.

[65] T. Shenkar and L. Wolf, "Anomaly detection for tabular data with internal contrastive learning," in *International Conference on Learning Representations*, 2021.

[66] L. Ruff, R. Vandermeulen, N. Goernitz, L. Deecke, S. A. Siddiqui, A. Binder, E. Müller, and M. Kloft, "Deep one-class classification," in *Proceedings of the 35th International Conference on Machine Learning*, vol. 80, pp. 4393–4402, 2018.

[67] H. Xu, G. Pang, Y. Wang, and Y. Wang, "Deep isolation forest for anomaly detection," *IEEE Transactions on Knowledge and Data Engineering*, pp. 1–14, 2023.

[68] H. Xu, Y. Wang, J. Wei, S. Jian, Y. Li, and N. Liu, "Fascinating supervisory signals and where to find them: Deep anomaly detection with scale learning," in *Proceedings of the 40th International Conference on Machine Learning*, ICML'23, JMLR.org, 2023.

[69] B. Liu, D. Wang, K. Lin, P.-N. Tan, and J. Zhou, "Rca: A deep collaborative autoencoder approach for anomaly detection," in *IJCAI: proceedings of the conference*, vol. 2021, p. 1505, NIH Public Access, 2021.

[70] C. Qiu, T. Pfrommer, M. Kloft, S. Mandt, and M. Rudolph, "Neural transformation learning for deep anomaly detection beyond images," in *International Conference on Machine Learning*, pp. 8703–8714, PMLR, 2021.

[71] Y. Zhao, Z. Nasrullah, and Z. Li, "Pyod: A python toolbox for scalable outlier detection," *Journal of Machine Learning Research*, vol. 20, no. 96, pp. 1–7, 2019.

A Related Work

We begin with a brief overview of general unsupervised AD for tabular data, which is the primary focus of this paper, followed by a review of AE-based AD methods. Finally, we present techniques related to the proposed LPR.

A.1 Unsupervised AD

AD methods can be broadly categorized into Deep Learning (DL)-based and non-DL-based detectors. Non-DL methods include density-based, statistical, clustering, neighborhood, ensemble, subspace, and classification-based techniques, which are generally interpretable but often struggle with complex data structures [9]. In contrast, DL-based detectors leverage architectures such as autoencoders, diffusion models [11], generative adversarial networks, graph neural networks, deep one-class models [12], contrastive learning, and self-supervised learning. These methods typically derive anomaly scores from training loss functions, offering greater capacity to model complex distributions at the cost of higher computational demands and reduced interpretability. A shared limitation of both categories is that they compute anomaly scores for each object independently, overlooking the crucial consistency between object similarity and score similarity, an aspect shown to be vital for detection performance. Several techniques have been developed to enhance these detectors including multi-detector enhancement [13], and single-detector enhancement [14, 15]. Recent AD techniques have been developed using data augmentation [13, 16, 17] and Decomposed Representation Learning (DRL) [1].

A.2 AE-based AD

AE-based anomaly detectors have been widely adopted for tabular data due to their ability to capture complex nonlinear structures in an unsupervised manner. Classical approaches such as the vanilla AE and Denoising Autoencoder (DAE) utilize reconstruction error as the anomaly score, based on the assumption that normal objects can be reconstructed accurately, while anomalies cannot. Extensions such as the Robust Deep Autoencoder (RDAE) incorporate robust loss functions or regularization terms to increase resilience against corrupted or noisy inputs. Probabilistic models like the Variational Autoencoder (VAE) [18] and its variant β-VAE [19] provide uncertainty estimates alongside reconstruction, which has shown utility in AD tasks.

These foundational models have spurred the development of many AE-based methods for tabular AD. More recently, advanced AE-based detectors have been proposed to address limitations such as model size [20], poor anomaly separation in reconstruction [4, 9, 21], and lack of interpretability [22]. For example, methods like SwitchTab [23] and AD-VAE [24] reflect a growing focus on improving robustness, generalizability, and interpretability in AE-based AD for tabular data.

Despite these advances, prior work has primarily focused on structural components such as the number of layers, latent space size, or activation functions. As summarized in Table A2, each component of the AE architecture contributes uniquely to its functionality. However, one crucial factor has been largely unexplored: **layer precision**. This paper fills that gap by revealing its critical role in **manifold pattern prioritization**, which is highly relevant for AD performance.

A.3 LPR-related techniques

Since LPR employs rounding to reduce layer precision, *rounding* and *precision reduction* are inherently related techniques.

Rounding is a simple, efficient, and widely adopted operation across numerous fields in computer science, including signal processing, information theory, and Artificial Intelligence (AI), owing to its utility in denoising, compression, and numerical alignment [25, 26]. Although extensively studied in applications such as Joint Photographic Experts Group (JPEG) compression and neural network quantization, the role of rounding in AD is relatively unexplored. In contrast to previous studies that utilize rounding primarily for reducing memory or computational costs, our proposed LPR leverages rounding to enhance the effectiveness of AD. Unlike dependent rounding approaches used in clustering algorithms [27], which operate on entire vectors to preserve distributional properties, LPR performs rounding on individual scalar values.

Table A1: Recent advances in AE-based anomaly detection

Key Ability	Techniques / Components	Representative Models
Robust Learning	Robust loss functions, noise-aware training, adversarial learning	Robust Deep AE [29], MemAE [4]
Stability	Regularization (dropout, weight decay), curriculum learning	CAE-SS [30], DAGMM [31], Fisher AE [5]
Generalizability	Disentangled representations, causal modeling, domain-invariant features	CRCL [6], Causal VAE [32],
Local/Global Sensitivity	Attention, multi-scale feature learning, dilated convolutions	Attention-AE [33], MemAE-GMM-MA [34], Conv AE [35]
Interpretability	Memory attention, heatmaps, prototype comparison	MemAE [4], ProtoVAE [7]
Diversity	Variation in normal and abnormal patterns, including multiple classes or feature representations	AADAE [36], AEVAE [37], MinMaxAD [38]
High-Dim/Sparse Handling	Sparsity-aware loss, latent compression, VAE	VAE [39], Sparse AE [40]
Computational Efficiency	Pruning, quantization, distilled architectures	compressed-AE [41], QAE [42]
Adversarial Resistance	Adversarial training, noise injection, defensive distillation	Defense-VAE [43], Robust Denoising AE [44]
Uncertainty Estimation	Bayesian inference, dropout-based sampling	VAE-based AD [45], BayesAE [46], Uncertainty-Aware AE [47, 48]
Scalability	Modular designs, parallel/distributed training	CAE-T [8], Scalable MemAE [4], Streaming-AE [49]
Manifold Pattern Prioritization (ours)	Prioritizing dominant manifold structures while suppressing low-density or rare components	LPR (ours)

Precision reduction techniques have traditionally been developed for model compression. As previously noted, quantization methods [10, 28] apply rounding for reducing bit-width representations in weights and activations. However, the proposed LPR fundamentally differs from quantization in both its formulation and motivation, as detailed in Section 3.2.

Simple Training-Time Mechanisms. LPR is related to a class of simple training-time mechanisms that introduce inductive biases with minimal changes to the training pipeline; however, it introduces a distinct form of inductive bias by directly constraining the numerical precision of trainable parameters. A broader comparison is provided in Section B.1.

B Technical details

B.1 Simple Training-Time Mechanisms

A number of widely adopted deep learning techniques are simple in implementation but influential because they introduce distinct inductive biases or alter training dynamics. Examples include dropout, weight decay, label smoothing, gradient clipping, learning-rate warmup, noise injection, and normalization methods. These methods typically require only minor changes to the training pipeline, yet they affect model capacity, stability, calibration, robustness, or generalization.

Table A3 summarizes these mechanisms. LPR follows this line of simple training-time mechanisms. However, unlike existing techniques that control learning through stochastic masking, parameter

Table A2: Structural Role Summary of Autoencoder Components

Component	Structural Role	Effect on Functionality
Layer Number	Controls depth and capacity of the network	Enables modeling of complex representations; deeper models may risk overfitting or instability
Activations	Introduce non-linearity to model complex patterns	Affect expressiveness, gradient flow, and convergence dynamics
Bias	Shifts neuron activation thresholds	Improves flexibility and breaks output symmetry
Loss Function	Defines reconstruction objective	Affects sensitivity to outliers and training stability
Outlier Scoring Function	Determines post-training anomaly detection mechanism	Impacts detection accuracy, false positive rates, and interpretability
Latent Space Size	Controls compression and abstraction level	Balances representation power vs. anomaly sensitivity
Normalization	Stabilizes and accelerates training	Reduces internal covariate shift, leading to better convergence
Dropout	Prevents neuron co-adaptation	Enhances generalization and reduces overfitting
Weight Initialization	Sets starting point for training	Impacts convergence speed and training dynamics
Optimizer/ Learning Rate	Governs model updates during training	Influences stability, convergence, and overall performance
Skip Connections	Facilitate information flow across layers	Preserve low-level features and improve gradient propagation
Regularization Losses	Impose constraints on weights or activations	Promote sparsity, generalization, and model simplicity
Noise Injection	Perturbs inputs or latent representations	Increases robustness to noise and adversarial conditions
Attention Mechanisms	Focus on informative features or regions	Improve interpretability and relevance of representations
Latent Prior	Imposes constraints on latent space distributions	Enables generative modeling and uncertainty estimation
Residual Blocks	Mitigate vanishing gradient problems	Allow deeper architectures with stable optimization
Decoder Design	Determines reconstruction pathway	Affects output quality and representational power
Training Strategy	Modulates exposure to data complexity	Affects convergence behavior and learning dynamics
Layer Precision	Adjusts numerical precision of weights and biases	Influences prioritization of dominant patterns over rare ones (i.e., anomalies)

shrinkage, output smoothing, gradient rescaling, or normalization, LPR controls learning through the numerical precision of trainable parameters. This reveals layer-level precision as a previously underexplored axis for shaping representation bias.

B.2 Training Algorithm

The modified training loop for LPR is as follows:

Table A3: Examples of simple training-time mechanisms and their induced effects.

Method	Main Operation	Primary Effect	Control Axis
Dropout	Randomly masks activations	Reduces co-adaptation	Stochastic activation sparsity
Weight Decay	Penalizes large weights	Controls parameter magnitude	Parameter norm
Label Smoothing	Softens target labels	Reduces overconfidence	Output distribution
Gradient Clipping	Bounds gradient norm	Stabilizes optimization	Gradient scale
Learning-rate Warmup	Gradually increases the Learning Rate (LR)	Stabilizes early training	Optimization schedule
Noise Injection	Adds random perturbations	Improves robustness	Stochastic perturbation
Batch/Layer Normalization	Normalizes activations	Stabilizes training dynamics	Activation statistics
Quantization-aware Training	Simulates low-bit inference	Preserves performance under quantization	Bit-level representation
LPR (ours)	Rounds trainable parameters during training	Suppresses fine-grained reconstruction	Parameter precision

Algorithm 1: Training AE with LPR

Input: Data $\{x_i\}_{i=1}^N$, epochs T, learning rate η, per-layer precisions $\{\Delta_\ell\}$
Initialize network parameters θ;
Project initial parameters: $\theta \leftarrow Q_\Delta(\theta)$;
for $t = 1$ **to** T **do**
  Compute outputs: $y_i = f_\theta(x_i)$;
  Compute loss: $\mathscr{L} = \frac{1}{Nm}\sum_i \|y_i - x_i\|_2^2$;
  Backpropagate: $g = \nabla_\theta \mathscr{L}$;
  Optimizer update: $\theta \leftarrow \text{OptUpdate}(\theta, g)$;
  Apply layer precision : $\theta \leftarrow Q_\Delta(\theta)$;
Output: Precision-constrained parameters θ

B.3 Discussion: precision, quantization, regularization, and limitations

Relation to Quantization LPR is closely related to quantization in its use of parameter discretization, but differs fundamentally in objective and training protocol. Standard quantization methods are applied either after training, as in post-training quantization (PTQ) [50], or during training or fine-tuning, as in quantization-aware training (QAT) [51], to reduce memory and computational cost while preserving the behavior of a full-precision model. In contrast, LPR introduces precision constraints during training, thereby altering the optimization trajectory and the resulting solution.

Post-training quantization approximates a trained model on a quantization grid, whereas QAT incorporates quantization into training. LPR imposes parameter-grid constraints during training to influence which patterns are reconstructed. In this sense, LPR explicitly targets precision-induced pattern prioritization, while conventional deployment-oriented quantization typically seeks to retain task performance. Thus, LPR serves as a training-time modeling strategy that controls learning behavior through parameter precision.

The contribution of LPR lies in using parameter precision as a mechanism to control learning capacity and influence pattern prioritization. Its contribution is the formulation and investigation of parameter precision as a capacity-control axis for anomaly detection, together with theoretical interpretation and empirical characterization. Our comparison with INT8 quantization-aware training provides an initial evaluation of LPR relative to conventional quantization approaches.

Relation to Regularization LPR can be viewed as a form of regularization in a broad sense, but differs from standard techniques such as weight decay [52], noise injection [53] or dropout [54] in how constraints are imposed. Conventional regularization methods introduce soft penalties or stochastic perturbations, encouraging generalization while largely preserving the function class.

In contrast, LPR directly constrains the parameter space through discretization, resulting in a structural restriction of the hypothesis class. This directly constrains the set of representable functions and influences the optimization dynamics. Importantly, LPR may improve anomaly detection performance precisely by reducing the model's effective capacity during training. By limiting the ability to fit low-density structures, it promotes the *manifold pattern prioritization* effect, where dominant patterns are preserved while anomalous components are suppressed in reconstruction.

Implications and Limitations LPR is most effective when the original model has excessive reconstruction capacity and tends to fit fine-grained or precision-sensitive structures. In such cases,

precision constraints act as an implicit structural regularizer, increasing the reconstruction gap between normal and anomalous samples.

However, its effectiveness depends on the alignment between data structure and precision sensitivity. If anomalous patterns can be represented using coarse or dominant structures, precision reduction may not improve separability. Moreover, overly coarse precision may degrade reconstruction of dominant patterns. A legitimate minority normal subgroup may also require fine parameter precision. Coarse projection can under-reconstruct this group and increase false positives; low density alone does not identify an anomaly.

Therefore, the precision level d_ℓ controls a trade-off between preserving dominant structures and suppressing precision-sensitive patterns. In practice, moderate precision reduction often achieves improved discriminability without significant loss of reconstruction fidelity.

Overall, LPR provides a simple training-time capacity constraint that aligns with the manifold pattern prioritization principle, offering a practical mechanism for improving reconstruction-based anomaly detection without modifying model architecture or loss functions.

B.4 Experimental setup

Datasets This study tests 30 publicly available real-world benchmark datasets for anomaly detection with anomaly annotations [55, 56], whose details are summarized in Table A4. The data are normalized between 0 and 1, after which all anomaly detection methods are applied.

Baseline We evaluate a total of 24 baseline methods, detailed in Table A5, and categorize them into two groups. The first group consists of 10 deep AD models: 5 unsupervised AE-based methods (AE [29], MCM [13], VAE [18], β-VAE [19], and PAE [9]), 2 unsupervised non-AE-based methods (DTE [11] and U-DRL [1]), 1 semi-supervised method (S-DRL [1]), 1 weakly-supervised method (FEAWAD [2]), and 1 fully-supervised method (MLP [3]). Our proposed LPR technique is applied to enhance these 10 deep AD models. The resulting enhanced detectors are then compared against the remaining 14 baseline methods (LOF [57], OCSVM [58], IForest [59], KNN [60], ECOD [61], MGBOD [62], ODHD [63], LDGOD [64], ICL [65], DeepSVDD [66], DIF [67], SLAD [68], RCA [69], and NeuTraL [70]) in the second group.

Evaluation metrics We use the area under the receiver operating characteristic curve (AUROC) and the area under the precision-recall curve (AUPRC) as evaluation metrics. Both AUROC and AUPRC range from 0 to 1, where higher values indicate better performance, and a score of 1 represents a perfect result. AUPRC denotes the trapezoidal area under the precision–recall curve. Constant scores receive a zero penalty in both reported metrics before aggregation and precision selection; this penalty is distinct from their standard metric values.

Implementation Implementation details and parameter settings are provided in Table A5 and Appendix C.3. Default parameters from the original literature were used [67, 71]. For all deep AD models, we employed 10 different random seeds (ranging from 0 to 9) to ensure robustness. Each detector retains its specified training configuration. Within each paired comparison, AE and LPR share the architecture, data, seed, and training settings except for the precision constraint.

Unsupervised models fit and score the benchmark data without training labels. S-DRL fits the normal subset and scores the full dataset. FEAWAD uses a sampled 10% of anomalies as labeled positives and treats the remaining samples as unlabeled. The supervised MLP uses stratified 60/20/20 training/validation/test splits with fixed split random state 0; training initialization varies over ten seeds. Oracle precision selection uses evaluation labels as described in Section 5.1.

Results Average results across 30 datasets are reported in Tables 1, 2, 4, and 5, while per-dataset and per-detector results are provided in Appendix D.

C Selection protocols and additional analyses

When a detector produces constant anomaly scores, both reported AUROC and AUPRC scores are assigned a penalty of zero before averaging or precision selection. Zero denotes this evaluation

Table A4: Information about 30 datasets

Name	Objects	Dim	Outlier	Name	Objects	Dim	Outlier
PenDigits	9868	16	20	Wine	129	13	10
Satimage	5803	36	71	Stamps	340	9	31
Shuttle	1013	9	13	Mnist	7603	100	700
WBC	454	9	10	PageBlocks	5393	10	510
Thyroid	3772	6	93	Vertebral	240	6	30
WDBC	367	30	10	Cardiotocography	2114	21	466
Optdigits	5216	64	150	WPBC	198	33	47
Waveform	3443	21	100	Satellite	6435	36	2036
Musk	3062	166	97	Pima	768	8	268
Vowels	1456	12	50	Breastw	683	9	239
Lymphography	148	3	6	Ionosphere	351	32	126
Glass	214	7	9	SpamBase	4207	57	1679
Wilt	4819	5	257	HeartDisease	270	13	120
Letter	1600	32	100	Arrhythmia	450	259	206
Annthyroid	7129	21	534	Parkinson	195	22	147

Table A5: Information about 24 baseline methods

Group	Baseline	Category	Key model	Venue	Year
First	AE [29]	DL	AutoEncoder	KDD	2017
	MCM [13]	DL	AutoEncoder	ICLR	2024
	DTE [11]	DL	Diffusion probability model	ICLR	2024
	VAE [18]	DL	AutoEncoder	ICLR	2014
	β-VAE [19]	DL	AutoEncoder	arXiv	2018
	PAE [9]	DL	AutoEncoder	Pattern Recogn.	2025
	U-DRL [1]	DL	Decomposed representation learning	ICLR	2025
	S-DRL [1]	DL	Decomposed representation learning	ICLR	2025
	FEAWAD [2]	DL	AutoEncoder	IEEE TNNLS	2021
	MLP [3]	DL	Multilayer perceptron	TNNLS	2013
Second	DeepSVDD [66]	DL	One-class classification	ICML	2018
	RCA [69]	DL	Autoencoder	IJCAI	2021
	NeuTraL [70]	DL	Self-supervised	ICML	2021
	ICL [65]	DL	Contrastive Learning	ICLR	2021
	SLAD [68]	DL	Scale learning	ICML	2023
	DIF [67]	DL	Ensemble	IEEE TKDE	2023
	LOF [57]	non-DL	Neighborhood	SIGMOD	2000
	KNN [60]	non-DL	Neighborhood	VLDB	1998
	IForest [59]	non-DL	Random forest	ICDM	2008
	OCSVM [58]	non-DL	Support vector machine	Neural Comput.	2001
	ECOD [61]	non-DL	Ensemble	IEEE TKDE	2022
	MGBOD [62]	non-DL	Fuzzy granule density	IEEE TKDE	2025
	ODHD [63]	non-DL	One-class classification	IEEE TC	2024
	LDGOD [64]	non-DL	Neighborhood	Pattern Recogn.	2025

The acronyms non-DL and DL denote non-deep learning and deep learning, respectively.

penalty, not the usual area value for a constant scorer. All candidates remain eligible, and the same penalized scores are used for fixed-precision, oracle, LODO, and subgroup results. No dataset or seed is removed.

C.1 Seed-wise and mean-first oracle protocols

For dataset j, seed s, precision d, and reported evaluation score M_{jsd} after applying the constant-score zero penalty, let $S = 10$ denote the number of random seeds. Seed-wise oracle selects the best precision for each seed and then averages: $\frac{1}{S}\sum_{s=1}^{S}\max_d M_{jsd}$. Mean-first oracle averages seeds before selecting precision: $\max_d \frac{1}{S}\sum_{s=1}^{S} M_{jsd}$. Selection uses test-set AUROC or AUPRC, separately for each metric. Main-paper oracle results use seed-wise selection. Tables A7 and A8 compare both protocols for the regularization/quantization and bottleneck experiments, respectively.

C.2 Sensitivity to constant-score handling

When a detector produces constant anomaly scores, both reported metrics are set to zero before averaging and precision selection. Without this penalty, a constant scorer has AUROC 50% and trapezoidal AUPRC $50(1+\pi)\%$, where π is the anomaly proportion in the evaluation set.

Table A6: Seed-wise and mean-first oracle results (mean ± pooled SD, %).

Detector	AUROC (seed-wise)	AUROC (mean-first)	AUPRC (seed-wise)	AUPRC (mean-first)
AE	72.15±18.99	70.15±20.06	40.34±29.10	39.10±29.26
MCM	77.89±18.28	75.40±19.81	47.01±29.82	44.01±30.47
DTE	75.92±15.63	69.67±19.37	45.28±29.98	40.50±29.99
VAE	71.67±18.17	70.86±18.88	39.13±29.41	38.62±29.45
β-VAE	71.69±18.16	70.88±18.84	39.17±29.42	38.61±29.45
PAE	83.06±14.16	80.19±16.56	49.47±31.02	45.64±30.90
U-DRL	78.61±17.30	76.16±18.47	46.43±30.61	43.82±31.22
S-DRL	82.33±16.14	80.40±16.82	55.40±31.67	52.65±31.72
FEAWAD	87.39±12.15	85.06±13.92	68.38±25.11	65.54±25.78
MLP	91.86±13.68	90.54±16.53	76.68±29.48	74.71±31.26

Table A7: Regularization and quantization under both oracle protocols (mean ± pooled SD, %).

Method	AUROC seed-wise	AUROC mean-first	AUPRC seed-wise	AUPRC mean-first
AE	65.00±21.07	65.00±21.07	35.28±28.78	35.28±28.78
Dropout	68.40±21.17	67.78±21.34	39.71±32.24	39.39±32.18
WeightDecay	65.00±21.07	65.00±21.07	35.29±28.78	35.29±28.78
Noise	66.23±21.14	65.87±21.19	36.60±29.37	36.27±29.11
PTQ	65.00±21.07	65.00±21.07	35.29±28.78	35.29±28.78
QAT	64.85±21.06	64.85±21.06	34.95±28.75	34.95±28.75
LPR	72.15±18.99	70.15±20.06	40.34±29.10	39.10±29.26

We also evaluate oracle selection by excluding constant-score candidates instead of penalizing them. Seed-wise selection excludes constant candidates separately for each seed. Mean-first selection considers only precisions that produce nonconstant scores in all ten seeds. Every case has an eligible candidate, so all datasets and seeds are retained.

The two treatments give identical oracle results for all ten detectors under both selection protocols, including the means and SDs in Table A6. Table A9 compares fixed-precision and LODO results with and without the zero penalty. For LODO, each treatment uses its own source-dataset AUROC values to select precision.

C.3 Quantization and regularization implementation

The AE comparison uses global min–max normalized inputs and the executed architecture $m \to m \to h \to m \to m$, with $h = \max(1, \lfloor m/2 \rfloor)$, bias terms, and ReLU after each executed linear layer, including the reconstruction layer. Training uses 100 full-batch epochs, Adam, MSE loss, and mean squared reconstruction-error scoring. Weight decay uses AdamW; LPR varies d from 0 to 6. All methods share the datasets and ten seeds. Table A10 lists the baseline configurations.

Dropout uses $p \in \{0.05, 0.1, 0.2\}$ after the first two hidden ReLU activations. QAT uses signed symmetric per-tensor INT8 fake quantization: $\alpha_q = \max|x|/127$ and $\hat{x} = \alpha_q \,\mathrm{clip}(\mathrm{round}(x/\alpha_q), -128, 127)$, with all-zero tensors mapped to zero. Training retains float32 master parameters and uses a straight-through estimator. Linear-layer weights and biases, together with hidden post-ReLU activations, are quantized during the forward pass. The output activation remains unquantized, and evaluation uses the same fake-quantized forward pass. LPR rounds weights and biases after initialization and each optimizer step to a fixed decimal grid, while retaining full-precision activations.

C.4 Leave-one-dataset-out evaluation

For held-out dataset j, let R_{ikd} denote the AUROC averaged over ten seeds for model i on source dataset k at precision d. We select

$$d_j = \underset{d \in \{0,\ldots,6\}}{\arg\max} \frac{1}{10 \cdot 29} \sum_{i=1}^{10} \sum_{k \neq j} R_{ikd},$$

Table A8: Bottleneck oracle results (mean ± pooled SD, %).

Bottleneck	Metric	Seed-wise	Mean-first
$h = 1$	AUROC	65.30±21.43	63.54±21.89
$h = 1$	AUPRC	34.12±27.22	32.89±26.97
$m/8$	AUROC	66.54±19.82	64.50±20.39
$m/8$	AUPRC	33.33±26.56	31.93±26.35
$m/4$	AUROC	70.58±18.71	68.06±19.79
$m/4$	AUPRC	37.90±28.72	36.37±28.85
$m/3$	AUROC	71.13±19.01	68.61±20.42
$m/3$	AUPRC	39.07±28.83	37.30±28.61
$m/2$	AUROC	72.15±18.99	70.15±20.06
$m/2$	AUPRC	40.34±29.10	39.10±29.26

Table A9: Standard metrics and zero-penalty report scores (%): mean ± SD over ten detectors, 30 datasets, and ten seeds. Standard denotes AUROC or AUPRC; Zero-penalty assigns zero to constant-score runs.

	AUROC		AUPRC	
Setting	Standard	Zero-penalty	Standard	Zero-penalty
$d = 0$	56.31±17.71	31.31±35.41	45.24±25.19	16.20±26.28
$d = 1$	58.86±22.94	53.47±29.35	33.56±28.69	27.21±28.72
$d = 2$	59.46±23.53	59.46±23.53	29.26±27.45	29.26±27.45
$d = 3$	69.54±22.79	69.54±22.79	40.91±31.56	40.91±31.56
$d = 4$	71.31±21.80	71.31±21.80	42.79±31.59	42.79±31.59
$d = 5$	71.67±21.41	71.67±21.41	43.13±31.59	43.13±31.59
$d = 6$	71.68±21.54	71.66±21.58	43.24±31.59	43.22±31.60
LODO	71.40±21.63	71.44±21.65	43.01±31.56	43.03±31.62

breaking exact ties toward the smaller d. The selected d_j is shared by all ten models and used for both AUROC and AUPRC on dataset j. Selection uses source-dataset labels, without using held-out labels. Tables A18–A27 report per-dataset results for all seven fixed precisions and all ten models. Tables A11–A13 report the selected precisions and held-out LODO results. Each overall per-dataset result is averaged equally across the ten models.

Table A10: Configuration of regularization and quantization baselines.

Method	Configuration
AE	Architecture: $m \to m \to \max(1, \lfloor m/2 \rfloor) \to m \to m$, with biases and ReLU after every executed layer, including the output.
Dropout	Linear $\to$ ReLU $\to$ Dropout(p), $p \in \{0.05, 0.1, 0.2\}$
Weight Decay	AdamW with weight decay $\lambda \in \{10^{-5}, 10^{-4}, 10^{-3}\}$
Noise	Gaussian input noise, $\sigma \in \{0.01, 0.05, 0.1\}$
PTQ	Post-training fake INT8 quantization of weights and biases before inference
QAT	Fake INT8 quantization of weights, biases, and hidden activations during training
LPR	Layer precision reduction with $d_\ell \in \{0, 1, 2, 3, 4, 5, 6\}$

Table A11: Per-dataset LODO selections and held-out results (mean ± SD, %). SD is pooled over ten models and ten seeds per model.

Dataset	Selected d	AUROC	AUPRC
PenDigits	5	63.42±16.06	6.28±18.24
Satimage	5	88.82±17.95	54.67±33.52
Shuttle	5	78.82±26.67	24.49±28.15
WBC	5	97.37±2.88	62.97±15.88
Thyroid	5	85.65±18.69	41.84±27.78
WDBC	5	90.99±9.88	62.22±19.96
Optdigits	5	56.24±23.85	20.87±36.64
Waveform	6	60.95±14.52	9.07±12.56
Musk	6	96.85±9.07	82.78±24.56
Vowels	5	79.79±14.27	31.11±28.53
Lymphography	5	83.58±14.18	59.97±21.64
Glass	5	65.61±19.12	12.22±8.33
Wilt	6	45.72±14.57	5.28±2.66
Letter	5	61.96±12.07	16.25±16.56
Annthyroid	5	63.14±14.62	19.91±17.99
Wine	6	73.77±29.89	38.41±30.18
Stamps	5	77.38±16.05	31.60±20.60
Mnist	5	74.56±14.04	37.18±25.10
PageBlocks	5	77.41±17.94	46.62±21.28
Vertebral	5	46.13±17.76	15.15±12.88
Cardiotocography	6	66.69±16.54	44.74±22.32
WPBC	5	53.68±12.10	28.55±13.87
Satellite	5	67.38±14.79	60.56±17.38
Pima	5	68.78±9.91	54.20±10.97
Breastw	5	89.88±19.29	88.92±17.27
Ionosphere	5	75.55±19.62	71.58±19.78
SpamBase	5	61.57±18.51	52.81±22.08
HeartDisease	5	67.70±16.20	64.87±14.69
Arrhythmia	6	64.15±7.71	62.59±9.03
Parkinson	5	59.68±22.10	83.18±10.17

C.5 Dataset heterogeneity and small-anomaly-count checks

Datasets are ranked by sample size, feature dimensionality, and anomaly count using the statistics in Table A4. For each characteristic, the ranking is split into two groups of 15 datasets, with ties resolved by their order in Table A4. Table A14 summarizes the subgroup characteristics; Tables A15 and A16 report oracle gains and fixed-precision differences, respectively.

Tables A56 and A57 report associations with the selected precision and detector–dataset improvement rates, respectively.

Table A12: LODO AUROC by detector and dataset (mean ± SD over ten seeds, %).

Dataset	AE	MCM	DTE	VAE	β-VAE	PAE	U-DRL	S-DRL	FEAWAD	MLP
PenDigits	58.66 ±16.39	62.71 ±7.70	63.12 ±7.47	57.12 ±3.73	57.14 ±3.72	76.08 ±13.43	53.89 ±7.65	56.11 ±11.92	95.30 ±5.95	54.06 ±15.50
Satimage	94.04 ±3.68	72.93 ±12.10	98.97 ±0.21	95.19 ±0.80	95.19 ±0.81	99.01 ±1.49	41.62 ±5.49	93.80 ±3.01	99.12 ±0.76	98.33 ±1.04
Shuttle	73.77 ±23.48	94.32 ±3.74	84.93 ±13.05	63.38 ±13.30	63.39 ±13.22	93.17 ±1.69	96.50 ±1.80	98.52 ±2.11	90.89 ±27.27	29.37 ±31.54
WBC	97.56 ±2.63	98.02 ±0.26	98.28 ±0.12	97.47 ±1.94	97.48 ±1.94	98.12 ±0.67	94.09 ±1.99	97.72 ±0.34	94.93 ±6.17	100.00 ±0.00
Thyroid	66.82 ±25.59	95.15 ±1.51	96.36 ±0.45	59.81 ±11.45	59.81 ±11.45	92.83 ±10.81	91.89 ±1.63	95.72 ±2.04	98.44 ±2.07	99.62 ±0.35
WDBC	95.64 ±1.36	97.54 ±0.43	64.59 ±3.52	90.84 ±2.43	91.40 ±2.08	90.83 ±6.44	88.50 ±1.55	95.81 ±1.23	94.76 ±4.38	100.00 ±0.00
Optdigits	53.64 ±15.63	29.92 ±18.14	37.12 ±4.32	48.16 ±3.52	48.15 ±3.47	60.00 ±11.39	44.64 ±5.11	45.64 ±2.91	95.20 ±4.46	99.98 ±0.01
Waveform	56.49 ±14.47	54.10 ±2.34	64.27 ±2.76	53.20 ±4.70	53.14 ±4.76	54.10 ±11.94	53.39 ±2.02	53.48 ±1.72	73.79 ±10.34	93.51 ±0.80
Musk	82.10 ±15.21	98.81 ±1.81	99.96 ±0.07	99.33 ±0.20	99.33 ±0.19	89.67 ±16.00	99.92 ±0.20	99.37 ±1.26	100.00 ±0.00	100.00 ±0.00
Vowels	64.71 ±15.71	78.02 ±6.76	76.25 ±3.04	66.27 ±7.05	66.28 ±7.04	72.73 ±11.06	88.23 ±3.94	94.71 ±1.78	91.27 ±5.09	99.40 ±0.79
Lymphography	66.71 ±25.44	72.15 ±4.85	83.51 ±1.59	82.53 ±9.55	82.55 ±9.61	78.69 ±17.22	91.30 ±2.58	92.93 ±1.47	86.76 ±3.65	98.62 ±3.16
Glass	43.79 ±20.25	70.53 ±5.75	67.70 ±6.76	44.60 ±15.03	45.56 ±14.13	71.96 ±5.82	78.42 ±6.23	78.41 ±4.33	62.43 ±13.74	92.68 ±0.94
Wilt	39.36 ±7.24	33.44 ±6.19	52.23 ±2.42	39.78 ±6.82	39.78 ±6.82	34.39 ±2.26	43.84 ±3.08	47.25 ±3.98	65.82 ±19.93	61.28 ±20.53
Letter	53.02 ±3.79	57.55 ±0.83	57.23 ±1.20	51.64 ±2.73	51.67 ±2.63	75.43 ±3.55	52.48 ±2.45	64.94 ±4.73	66.52 ±3.03	89.11 ±1.99
Annthyroid	48.53 ±6.97	57.50 ±1.19	64.13 ±7.02	51.23 ±1.93	51.23 ±1.93	63.05 ±5.70	54.84 ±0.83	62.25 ±1.56	86.43 ±2.29	92.23 ±1.12
Wine	86.34 ±9.34	91.17 ±5.48	21.29 ±21.42	84.78 ±7.12	83.77 ±6.86	24.81 ±31.01	71.16 ±8.53	96.60 ±2.67	77.74 ±12.50	100.00 ±0.00
Stamps	62.00 ±16.96	80.14 ±9.63	81.57 ±5.24	56.68 ±9.93	56.73 ±10.19	89.33 ±2.48	78.25 ±4.81	87.59 ±5.87	84.10 ±9.42	97.42 ±0.92
Mnist	69.41 ±5.03	78.20 ±4.17	58.63 ±3.86	68.41 ±1.26	68.41 ±1.28	85.46 ±1.04	57.14 ±3.46	66.86 ±7.75	93.80 ±2.26	99.27 ±0.17
PageBlocks	50.15 ±13.94	92.78 ±1.59	64.95 ±11.14	57.12 ±2.58	57.13 ±2.58	89.50 ±1.22	85.45 ±3.95	93.24 ±1.86	90.09 ±4.24	93.68 ±1.02
Vertebral	31.78 ±7.55	43.54 ±5.96	49.09 ±4.45	34.63 ±7.38	34.69 ±7.30	42.32 ±8.96	32.57 ±2.11	38.14 ±3.97	73.71 ±10.06	80.79 ±4.84
Cardiotocography	66.29 ±10.36	61.48 ±8.70	67.22 ±6.76	60.88 ±3.80	60.87 ±3.77	48.33 ±8.75	50.58 ±1.34	60.86 ±3.16	91.86 ±3.94	98.57 ±0.17
WPBC	54.62 ±2.17	54.90 ±0.54	41.27 ±1.44	52.64 ±3.27	52.39 ±3.35	47.50 ±4.49	43.88 ±1.94	46.74 ±2.94	57.00 ±2.47	85.88 ±2.58
Satellite	49.41 ±3.06	49.16 ±10.46	75.00 ±1.21	59.23 ±0.64	59.22 ±0.63	74.98 ±4.71	56.41 ±6.31	73.31 ±1.21	85.08 ±4.17	92.01 ±2.77
Pima	73.51 ±3.79	68.92 ±3.46	57.86 ±2.53	69.99 ±3.60	69.95 ±3.59	62.03 ±3.90	53.24 ±1.01	67.28 ±1.42	76.14 ±3.37	88.91 ±0.44
Breastw	98.51 ±0.93	98.21 ±0.38	79.27 ±5.46	98.32 ±0.53	98.32 ±0.52	96.27 ±1.30	34.93 ±2.40	98.88 ±0.12	97.07 ±2.81	98.99 ±0.04
Ionosphere	51.25 ±4.87	41.24 ±11.79	87.51 ±1.28	69.41 ±2.21	69.45 ±1.81	94.22 ±3.75	89.05 ±4.17	93.77 ±1.51	64.10 ±16.29	95.52 ±0.89
SpamBase	57.94 ±1.72	52.51 ±3.04	36.23 ±9.60	51.99 ±0.82	51.99 ±0.82	53.96 ±1.79	51.63 ±2.27	71.64 ±2.98	90.13 ±2.58	97.66 ±0.13
HeartDisease	78.65 ±5.22	79.25 ±7.45	41.64 ±7.21	68.87 ±5.56	68.68 ±5.74	49.53 ±15.96	50.76 ±3.60	81.00 ±2.23	72.96 ±8.43	85.67 ±1.16
Arrhythmia	59.74 ±3.84	58.13 ±5.58	59.20 ±3.96	56.60 ±2.36	56.67 ±2.26	72.88 ±0.80	65.23 ±1.69	66.59 ±3.43	67.83 ±2.97	78.58 ±0.55
Parkinson	65.38 ±8.77	75.59 ±4.27	25.41 ±4.55	47.97 ±4.26	48.25 ±3.96	56.79 ±19.05	36.60 ±5.94	87.49 ±1.72	58.55 ±7.48	94.76 ±1.77

Table A13: LODO AUPRC by detector and dataset (mean ± SD over ten seeds, %).

Dataset	AE	MCM	DTE	VAE	β-VAE	PAE	U-DRL	S-DRL	FEAWAD	MLP
PenDigits	0.29 ±0.20	0.31 ±0.06	0.27 ±0.06	0.30 ±0.07	0.30 ±0.07	0.52 ±0.22	0.28 ±0.07	0.37 ±0.27	59.84 ±11.77	0.27 ±0.13
Satimage	68.68 ±19.14	10.17 ±20.69	82.22 ±6.85	37.06 ±12.96	37.11 ±13.03	65.91 ±23.05	0.95 ±0.08	65.41 ±19.94	89.91 ±2.07	89.27 ±0.98
Shuttle	12.99 ±10.51	20.63 ±11.14	14.29 ±5.39	5.49 ±3.94	5.51 ±3.93	15.00 ±2.34	23.99 ±7.58	45.00 ±13.87	87.58 ±29.60	14.41 ±30.56
WBC	66.77 ±6.41	43.58 ±7.43	66.12 ±1.33	64.91 ±6.82	65.04 ±6.66	53.79 ±12.79	53.91 ±7.58	60.84 ±2.31	54.77 ±9.49	100.00 ±0.00
Thyroid	25.20 ±19.62	38.37 ±9.81	41.62 ±2.17	12.70 ±5.98	12.70 ±5.98	38.75 ±12.67	22.16 ±5.90	51.93 ±13.17	83.74 ±10.50	91.19 ±1.03
WDBC	59.38 ±11.21	70.02 ±1.98	45.04 ±4.00	57.62 ±4.02	57.74 ±4.01	26.35 ±9.55	67.34 ±5.31	76.65 ±3.10	62.09 ±18.00	100.00 ±0.00
Optdigits	3.24 ±1.24	2.01 ±0.47	2.07 ±0.15	2.59 ±0.19	2.59 ±0.19	3.54 ±1.16	2.46 ±0.24	2.55 ±0.11	88.21 ±7.36	99.43 ±0.12
Waveform	3.84 ±1.48	3.09 ±0.19	4.62 ±0.44	3.27 ±0.51	3.28 ±0.53	7.12 ±10.38	3.36 ±0.47	3.22 ±0.37	15.42 ±3.85	43.48 ±2.34
Musk	45.11 ±23.59	76.64 ±19.32	99.02 ±1.80	82.02 ±3.81	82.07 ±3.78	54.78 ±38.15	97.43 ±6.58	90.76 ±13.91	99.99 ±0.04	100.00 ±0.00
Vowels	12.00 ±14.40	16.61 ±8.94	16.65 ±2.31	9.63 ±4.22	9.46 ±4.27	13.68 ±8.89	23.56 ±9.40	49.82 ±11.33	70.24 ±8.90	89.47 ±8.71
Lymphography	46.12 ±28.17	36.44 ±16.45	66.27 ±1.13	59.93 ±13.75	60.04 ±13.81	60.82 ±19.50	50.98 ±7.39	75.73 ±0.87	59.58 ±7.57	83.75 ±32.62
Glass	4.23 ±1.75	9.14 ±4.59	7.51 ±0.99	4.31 ±1.71	4.41 ±1.76	8.30 ±0.71	16.29 ±4.87	22.14 ±3.24	23.91 ±6.48	22.00 ±1.95
Wilt	4.02 ±0.45	3.66 ±0.36	5.31 ±0.28	4.12 ±0.52	4.12 ±0.52	3.70 ±0.13	4.44 ±0.23	4.73 ±0.41	10.44 ±3.96	8.24 ±2.86
Letter	7.29 ±1.30	7.65 ±0.24	9.40 ±0.36	6.63 ±0.62	6.62 ±0.56	18.74 ±5.32	8.77 ±0.82	16.26 ±4.93	18.18 ±3.12	62.98 ±6.45
Annthyroid	8.45 ±1.40	10.60 ±0.36	18.36 ±7.51	7.89 ±0.48	7.90 ±0.49	10.81 ±1.22	9.18 ±0.38	23.21 ±1.73	39.09 ±13.19	63.57 ±2.73
Wine	32.36 ±17.68	37.39 ±9.78	5.54 ±2.98	31.22 ±11.54	32.54 ±13.94	8.18 ±7.89	14.95 ±4.92	66.25 ±20.76	55.72 ±17.53	100.00 ±0.00
Stamps	16.60 ±7.71	26.91 ±9.53	24.30 ±4.32	13.43 ±3.48	13.66 ±3.63	31.82 ±2.87	22.25 ±3.05	36.39 ±10.83	52.05 ±12.12	78.61 ±8.76
Mnist	28.41 ±2.34	32.49 ±2.93	15.60 ±3.06	24.07 ±1.08	24.07 ±1.09	39.95 ±1.80	12.57 ±0.95	26.85 ±6.82	74.24 ±6.14	93.59 ±0.55
PageBlocks	28.95 ±12.15	61.87 ±2.95	40.44 ±12.65	15.89 ±2.52	15.91 ±2.54	51.71 ±2.76	46.19 ±5.71	68.13 ±4.74	61.34 ±10.20	75.80 ±2.18
Vertebral	8.67 ±0.89	10.25 ±1.02	11.28 ±0.97	9.03 ±0.90	9.03 ±0.89	10.13 ±1.50	8.60 ±0.22	9.31 ±0.55	47.36 ±12.07	27.87 ±7.03
Cardiotocography	38.14 ±8.85	33.51 ±8.25	42.28 ±4.38	31.75 ±4.17	31.73 ±4.16	34.51 ±4.03	25.64 ±1.40	36.83 ±3.67	77.34 ±6.58	95.70 ±0.35
WPBC	25.14 ±1.72	24.75 ±0.59	20.02 ±0.45	24.05 ±2.04	23.96 ±1.85	22.06 ±1.77	20.43 ±0.96	21.97 ±1.61	35.74 ±3.42	67.38 ±6.52
Satellite	43.12 ±8.20	39.33 ±15.11	69.27 ±2.22	49.55 ±2.48	49.55 ±2.47	65.49 ±5.90	46.74 ±4.56	73.95 ±1.48	79.85 ±2.50	88.76 ±3.00
Pima	57.86 ±4.09	50.76 ±4.37	43.60 ±1.53	54.98 ±2.51	54.88 ±2.42	46.29 ±2.31	39.82 ±0.90	54.24 ±1.66	59.15 ±4.64	80.46 ±1.20
Breastw	97.62 ±1.27	93.97 ±1.76	76.83 ±4.62	97.36 ±0.81	97.37 ±0.78	94.47 ±1.54	40.86 ±0.73	97.63 ±0.24	95.01 ±4.83	98.10 ±0.06
Ionosphere	51.26 ±4.82	37.97 ±12.31	82.70 ±1.22	59.83 ±4.75	59.62 ±4.29	90.97 ±5.64	83.84 ±6.23	91.43 ±2.14	63.89 ±13.33	94.28 ±0.98
SpamBase	42.67 ±1.09	39.70 ±1.61	32.72 ±5.05	39.63 ±0.47	39.63 ±0.47	40.58 ±1.42	38.57 ±1.69	70.29 ±2.81	87.49 ±2.47	96.85 ±0.35
HeartDisease	72.14 ±6.09	73.43 ±10.17	44.13 ±5.05	62.81 ±6.33	62.63 ±6.19	48.91 ±9.69	48.05 ±2.69	79.25 ±3.51	72.66 ±5.47	84.71 ±2.11
Arrhythmia	60.83 ±3.83	57.53 ±4.43	61.40 ±4.37	50.35 ±2.74	50.33 ±2.64	70.91 ±0.75	62.38 ±2.42	63.49 ±2.49	69.19 ±2.26	79.47 ±0.54
Parkinson	87.10 ±4.24	92.08 ±1.68	67.32 ±2.93	77.49 ±2.48	77.63 ±2.22	81.42 ±8.86	73.90 ±2.97	95.87 ±0.60	80.96 ±4.59	98.04 ±0.66

Table A14: All three dataset descriptors in each ranked subgroup (Min: minimum; Max: maximum).

Ranked by	Group	Descriptor	Min	Mean	Max
Sample count	Bottom 15	Samples	129.00	388.00	1013.00
Sample count	Bottom 15	Features	3.00	30.80	259.00
Sample count	Bottom 15	Anomalies	6.00	84.80	268.00
Sample count	Top 15	Samples	1456.00	4794.67	9868.00
Sample count	Top 15	Features	5.00	40.20	166.00
Sample count	Top 15	Anomalies	20.00	457.53	2036.00
Feature count	Bottom 15	Samples	129.00	1971.13	9868.00
Feature count	Bottom 15	Features	3.00	9.00	16.00
Feature count	Bottom 15	Anomalies	6.00	111.07	510.00
Feature count	Top 15	Samples	195.00	3211.53	7603.00
Feature count	Top 15	Features	21.00	62.00	259.00
Feature count	Top 15	Anomalies	10.00	431.27	2036.00
Anomaly count	Bottom 15	Samples	129.00	2033.80	9868.00
Anomaly count	Bottom 15	Features	3.00	25.07	166.00
Anomaly count	Bottom 15	Anomalies	6.00	39.80	100.00
Anomaly count	Top 15	Samples	195.00	3148.87	7603.00
Anomaly count	Top 15	Features	5.00	45.93	259.00
Anomaly count	Top 15	Anomalies	100.00	502.53	2036.00

Subgroup and low-anomaly-count exclusion analyses use mean-first oracle selection: scores are averaged over ten seeds before selecting d separately for each dataset and metric. A fixed-precision comparison across all ten models additionally reports the performance difference between $d = 5$ and $d = 6$.

Table A15: Mean-first oracle subgroup gains across ten models (percentage points).

Characteristic	Group	Macro AUROC	Weighted AUROC	Macro AUPRC	Weighted AUPRC
Sample count	Top 15	4.63	4.71	4.25	3.76
Sample count	Bottom 15	5.91	5.62	5.95	5.83
Feature count	Top 15	4.66	4.34	4.21	4.36
Feature count	Bottom 15	5.88	5.51	5.98	3.19
Anomaly count	Top 15	5.65	4.44	4.00	2.63
Anomaly count	Bottom 15	4.89	5.31	6.20	5.91

Table A16: Fixed-$d = 5$ minus $d = 6$ subgroup differences (percentage points).

Characteristic	Group	Macro AUROC	Weighted AUROC	Macro AUPRC	Weighted AUPRC
Sample count	Top 15	-0.0880	-0.2705	-0.1008	-0.1923
Sample count	Bottom 15	0.1190	-0.0078	-0.0879	-0.1134
Feature count	Top 15	-0.0872	-0.2233	-0.1005	-0.1901
Feature count	Bottom 15	0.1182	-0.2957	-0.0883	-0.1803
Anomaly count	Top 15	-0.2158	-0.3456	-0.1696	-0.3709
Anomaly count	Bottom 15	0.2468	-0.1041	-0.0191	0.0993

Excluding the seven datasets with fewer than 30 anomalies leaves 23 datasets. On the remaining 23 datasets, the baseline achieves average AUROC and AUPRC of 69.33% and 44.66%, respectively. With mean-first oracle precision selection, LPR achieves 74.62% AUROC and 49.40% AUPRC. Fixed $d = 5$ minus $d = 6$ is -0.0658 AUROC percentage points and -0.0867 AUPRC percentage points.

C.6 Bottleneck dimensionality and capacity controls

The AE architecture is $m \to m \to h \to m \to m$, with ReLU after each executed layer. The default bottleneck is $h = \max(1, \lfloor m/2 \rfloor)$. Labels m/k denote $h = \max(1, \lfloor m/k \rfloor)$. Only h varies; all other

training settings are fixed. AE and LPR share the architecture at each bottleneck. The analysis below uses mean-first oracle selection. Table A17 reports the bottleneck comparison, with gains in Percentage Points (pp). Oracle gains range from 1.42 to 5.16 AUROC percentage points and 1.02 to 3.82 AUPRC percentage points. Fixed $d = 5$ remains close to AE. Selecting both h and d using test-set performance gives gains of 2.64 AUROC percentage points and 2.25 AUPRC percentage points. This ablation evaluates LPR across explicit bottleneck sizes; identifying model-specific effective capacity boundaries remains a direction for future work.

Table A17: Bottleneck results under mean-first oracle selection (%).

Bottleneck	Metric	AE	Oracle LPR	Gain (pp)
$h = 1$	AUROC	62.12	63.54	1.42
$h = 1$	AUPRC	31.79	32.89	1.09
$m/8$	AUROC	61.69	64.50	2.81
$m/8$	AUPRC	30.82	31.93	1.10
$m/4$	AUROC	66.18	68.06	1.88
$m/4$	AUPRC	35.36	36.37	1.02
$m/3$	AUROC	65.37	68.61	3.24
$m/3$	AUPRC	34.65	37.30	2.64
$m/2$	AUROC	64.99	70.15	5.16
$m/2$	AUPRC	35.28	39.10	3.82

C.7 Computational cost and deployment scope

For fixed d, the projection is one element-wise operation over trainable parameters after each optimizer step, with complexity $O(|\theta|)$ and no additional forward/backward pass. Testing K values costs approximately K independent training runs. Inference uses the original architecture without an extra projection step. Rounding floating-point parameters does not itself reduce their storage datatype, model memory, or inference runtime. Potential savings from an explicitly changed datatype depend on implementation and hardware.

D Detailed methods and experimental results

D.1 The Proposed Method

D.1.1 Comparison with Standard AE Code

The key change is a projection step after each gradient update:

$$\theta \leftarrow Q_\Delta(\theta)$$

which rounds all weights/biases to a fixed decimal precision.

```
import torch
from torch import nn

class AE(nn.Module):
    def __init__(self, m):
        super().__init__()
        h = max(1, m//2)
        self.layers = nn.ModuleList([
            nn.Linear(m, m), nn.Linear(m, h),
            nn.Linear(h, m), nn.Linear(m, m)])
    def forward(self, x):
        for layer in self.layers:
            x = torch.relu(layer(x))
        return x

@torch.no_grad()
def project_parameters(model, d):
    scale = 10.0 ** d
    for parameter in model.parameters():
        parameter.copy_(torch.round(parameter * scale) / scale)

model = AE(m)
```

```
optimizer = torch.optim.Adam(model.parameters())
project_parameters(model, d) # introduced by LPR
for epoch in range(100):
    optimizer.zero_grad()
    loss = ((model(data) - data) ** 2).mean()
    loss.backward()
    optimizer.step()
    project_parameters(model, d) # introduced by LPR
```

An unprojected AE omits the projection step, as illustrated below.

```
for e in range(epochs):
  optimizer.zero_grad()
  loss = ((model(data) - data) ** 2).mean()
  loss.backward()
  optimizer.step()
```

This rounding step enforces precision constraints, acting as a form of parameter projection that can regularize the model. The code above is for illustration only.

D.2 Experimental Evaluation

D.2.1 Comparison with the First Baseline Group

Tables A18–A27 supplement Table 1 in the main paper, providing AUROC and AUPRC results for each detector on each dataset, averaged over 10 random seeds.

D.2.2 AE component ablations

Tables A28–A47 provide the per-dataset results for Table 4.

D.2.3 Comparison with the Second Baseline Group

Table A48 supplements Table 2, reporting per-dataset AUROC and AUPRC for each detector. LOF, OCSVM, IForest, KNN, ECOD, MGBOD, ODHD, and LDGOD are evaluated in a single run, while ICL, DeepSVDD, DIF, SLAD, RCA, and NeuTraL report means and standard deviations over ten random seeds.

D.2.4 Analysis of LPR's Mechanism

Table A49 supplements Table 5, presenting results using one specified seed per dataset and the test-label-selected d_ℓ values.

Table A18: AE's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	65.06±3.79	65.15±3.68	58.70±18.44	58.65±16.41	58.66±16.39	58.66±16.40
Sati.	67.11±0.00	72.70±2.23	72.45±2.14	93.44±3.89	94.07±3.69	94.04±3.68	94.04±3.68
Shut.	86.93±0.00	78.72±27.14	77.98±29.15	74.13±22.78	73.51±23.72	73.77±23.48	73.76±23.50
WBC	98.65±0.00	85.30±17.37	84.52±18.01	97.62±2.51	97.56±2.63	97.56±2.63	97.56±2.63
Thyr.	51.75±16.09	74.71±24.83	73.71±25.94	66.32±25.33	66.80±25.59	66.82±25.59	66.82±25.59
WDBC	97.68±0.00	97.22±0.57	97.19±0.50	95.64±1.30	95.63±1.34	95.64±1.36	95.64±1.36
Optd.	59.10±0.00	49.21±19.74	50.34±17.39	53.40±15.94	53.66±15.69	53.64±15.63	53.57±15.56
Wave.	51.22±0.00	56.66±8.32	56.02±7.95	57.27±13.88	56.50±14.48	56.49±14.47	56.49±14.47
Musk	11.94±0.00	22.46±5.66	17.63±2.87	79.68±15.60	82.36±15.01	82.12±15.23	82.10±15.21
Vowe.	90.15±0.00	80.95±8.06	81.52±8.03	65.27±15.34	64.70±15.71	64.71±15.71	64.70±15.71
Lymp.	55.34±31.95	62.98±26.74	61.65±27.33	67.38±25.37	66.76±25.49	66.71±25.44	66.71±25.44
Glass	26.88±13.60	31.65±13.68	31.18±13.19	42.99±20.18	43.76±20.27	43.79±20.25	43.79±20.24
Wilt	39.47±8.13	40.43±10.08	40.22±10.48	39.29±7.51	39.34±7.22	39.36±7.24	39.36±7.24
Lett.	56.33±0.00	55.79±0.80	55.79±0.75	52.75±3.51	53.08±3.82	53.02±3.79	53.03±3.79
Annt.	44.18±0.00	58.68±9.33	59.36±9.35	51.39±7.49	48.55±6.93	48.53±6.97	48.53±6.97
Wine	95.80±0.00	93.29±2.47	93.50±2.42	87.24±7.58	86.42±9.16	86.34±9.34	86.34±9.34
Stam.	66.81±0.00	65.16±14.80	65.41±14.80	62.12±16.89	62.02±16.93	62.00±16.96	62.00±16.96
Mnist	58.28±0.00	76.04±8.82	76.77±8.68	69.48±4.95	69.46±5.21	69.41±5.03	69.37±5.08
Page.	70.92±0.00	41.65±12.59	42.12±13.48	50.55±14.03	50.19±13.93	50.15±13.94	50.16±13.94
Vert.	35.04±6.00	34.44±12.88	33.73±11.62	31.78±7.28	31.78±7.55	31.78±7.55	31.77±7.54
Card.	60.06±0.00	62.02±8.09	61.54±7.61	66.42±10.35	66.30±10.36	66.29±10.36	66.29±10.36
WPBC	56.47±0.00	55.53±0.72	55.55±0.76	54.25±2.13	54.45±2.08	54.62±2.17	54.45±2.07
Sate.	38.03±0.00	39.75±0.82	39.64±0.76	49.43±3.18	49.37±3.08	49.41±3.06	49.41±3.06
Pima	76.08±0.00	74.13±2.73	74.33±2.75	73.51±3.78	73.51±3.80	73.51±3.79	73.51±3.79
Brea.	99.53±0.00	93.91±8.23	95.01±5.51	98.54±0.87	98.52±0.93	98.51±0.93	98.51±0.93
Iono.	32.83±0.00	33.98±0.74	33.95±0.77	51.08±4.80	51.26±4.87	51.25±4.87	51.52±4.68
Spam.	60.31±0.00	42.00±8.29	42.67±8.78	57.89±1.80	57.85±1.67	57.94±1.72	57.94±1.72
Hear.	85.21±0.00	82.90±2.02	83.49±2.02	79.52±5.44	78.64±5.20	78.65±5.22	78.65±5.22
Arrh.	55.38±0.00	55.34±0.43	55.29±0.47	59.25±4.20	59.64±4.40	60.13±4.37	59.74±3.84
Park.	79.08±0.00	75.59±4.36	75.96±3.43	65.27±8.85	65.36±8.83	65.38±8.77	65.39±8.78

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.34±0.07	0.34±0.06	0.30±0.20	0.29±0.20	0.29±0.20	0.29±0.20
Sati.	1.89±0.00	3.99±1.82	3.75±1.39	65.13±21.61	68.84±19.14	68.68±19.14	68.68±19.14
Shut.	17.14±0.00	16.94±12.71	17.29±12.81	13.19±10.87	12.98±10.52	12.99±10.51	12.99±10.51
WBC	70.28±0.00	51.08±16.83	52.06±15.14	66.64±6.44	66.77±6.43	66.77±6.41	66.77±6.41
Thyr.	16.99±20.81	32.30±23.82	32.90±25.31	24.41±18.80	25.19±19.60	25.20±19.62	25.21±19.63
WDBC	70.66±0.00	66.88±3.17	66.93±3.25	59.28±10.29	59.24±11.00	59.38±11.21	59.46±11.25
Optd.	3.41±0.00	3.23±1.75	3.10±1.55	3.24±1.26	3.25±1.24	3.24±1.24	3.24±1.24
Wave.	2.88±0.00	3.52±0.94	3.45±0.90	3.87±1.43	3.84±1.49	3.84±1.48	3.84±1.48
Musk	1.72±0.00	2.81±1.25	2.19±0.45	41.34±24.49	44.56±21.96	45.15±23.64	45.11±23.59
Vowe.	39.78±0.00	21.51±16.16	22.34±16.59	12.22±14.59	12.00±14.39	12.00±14.40	12.00±14.40
Lymp.	43.92±27.87	45.32±28.11	45.21±28.14	46.21±28.03	46.56±28.52	46.12±28.17	46.12±28.17
Glass	3.37±1.90	3.12±0.77	3.07±0.70	4.22±1.78	4.23±1.75	4.23±1.75	4.23±1.75
Wilt	4.06±0.63	4.17±0.78	4.17±0.88	4.02±0.49	4.01±0.45	4.02±0.45	4.02±0.45
Lett.	7.42±0.00	7.33±0.17	7.32±0.15	7.14±1.21	7.30±1.31	7.29±1.30	7.29±1.30
Annt.	7.43±0.00	13.16±6.01	13.20±5.66	9.12±1.57	8.45±1.39	8.45±1.40	8.45±1.40
Wine	49.35±0.00	41.68±7.30	42.32±7.06	32.86±17.49	32.38±17.65	32.36±17.68	32.36±17.68
Stam.	15.64±0.00	17.00±5.38	17.04±5.48	16.72±7.84	16.61±7.71	16.60±7.71	16.61±7.71
Mnist	22.31±0.00	34.27±10.91	34.53±9.72	28.30±2.37	28.47±2.38	28.41±2.34	28.39±2.36
Page.	35.38±0.00	24.09±10.86	23.80±11.68	28.87±12.49	28.96±12.16	28.95±12.15	28.95±12.14
Vert.	9.08±0.96	9.38±2.17	9.18±1.85	8.65±0.84	8.67±0.89	8.67±0.89	8.67±0.89
Card.	28.82±0.00	33.04±4.22	32.64±3.86	38.40±9.02	38.15±8.86	38.14±8.85	38.14±8.85
WPBC	25.68±0.00	25.09±0.44	25.10±0.47	24.90±1.74	25.07±1.75	25.14±1.72	25.07±1.74
Sate.	24.44±0.00	25.38±0.61	25.30±0.47	42.85±7.89	42.94±8.17	43.12±8.20	43.12±8.21
Pima	61.69±0.00	59.13±2.69	59.33±2.63	57.82±4.08	57.86±4.10	57.86±4.09	57.86±4.09
Brea.	99.11±0.00	93.71±7.46	94.70±5.05	97.66±1.19	97.63±1.26	97.62±1.27	97.62±1.27
Iono.	30.87±0.00	31.86±0.52	31.86±0.52	51.28±4.82	51.27±4.84	51.26±4.82	51.31±4.82
Spam.	44.11±0.00	35.74±3.96	35.98±4.26	42.63±1.17	42.62±1.05	42.67±1.09	42.67±1.09
Hear.	81.29±0.00	78.06±2.43	78.72±2.33	73.33±5.75	72.13±6.07	72.14±6.09	72.15±6.09
Arrh.	56.00±0.00	56.25±0.31	55.97±0.38	60.11±4.06	60.75±4.20	61.13±4.25	60.83±3.83
Park.	93.37±0.00	91.86±1.65	92.07±1.22	86.98±4.24	87.08±4.26	87.10±4.24	87.10±4.24

Table A19: MCM's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	58.61±20.51	65.15±3.11	63.89±5.76	61.59±9.83	62.71±7.70	70.46±11.87
Sati.	67.11±0.00	97.66±6.55	66.52±0.33	79.50±15.68	83.39±15.17	72.93±12.10	78.35±15.63
Shut.	86.93±0.00	59.94±28.60	86.91±8.42	87.30±16.95	90.48±7.36	94.32±3.74	91.95±4.88
WBC	98.65±0.00	98.64±0.02	97.69±0.62	97.70±0.34	97.82±0.36	98.02±0.26	97.83±0.26
Thyr.	45.04±0.00	92.59±4.94	91.85±3.66	95.46±1.19	95.34±1.63	95.15±1.51	95.63±1.60
WDBC	97.68±0.00	97.68±0.04	97.23±0.38	97.40±0.50	97.18±0.60	97.54±0.43	96.92±0.96
Optd.	59.10±0.00	78.54±21.52	46.41±2.89	52.32±10.98	37.26±18.23	29.92±18.14	36.54±20.29
Wave.	51.22±0.00	57.69±6.37	52.39±0.65	53.98±1.82	53.18±1.38	54.50±2.77	54.10±2.34
Musk	11.94±0.00	99.03±2.72	84.58±14.99	91.94±9.19	97.66±2.91	99.65±0.32	98.81±1.81
Vowe.	90.15±0.00	73.30±10.12	60.46±24.81	71.05±15.44	77.83±10.08	78.02±6.76	80.38±8.10
Lymp.	73.53±0.00	73.53±0.00	80.05±6.18	77.73±5.84	74.44±4.47	72.15±4.85	75.09±5.18
Glass	20.22±0.00	19.48±1.71	52.03±21.27	68.21±8.42	69.30±7.59	70.53±5.75	73.14±4.71
Wilt	32.45±0.00	34.59±9.61	31.22±4.62	32.64±1.99	34.33±4.83	36.41±7.07	33.44±6.19
Lett.	56.33±0.00	53.73±3.82	57.79±0.73	57.26±0.58	57.06±1.84	57.55±0.83	57.13±1.69
Annt.	44.18±0.00	56.90±1.98	55.85±6.92	58.36±2.99	56.90±3.29	57.50±1.19	57.31±0.75
Wine	95.80±0.00	95.67±0.16	93.13±4.08	92.88±3.19	93.26±5.23	93.82±3.44	91.17±5.48
Stam.	66.81±0.00	66.82±0.46	75.43±19.78	79.69±9.23	80.22±12.03	80.14±9.63	84.35±6.27
Mnist	58.28±0.00	79.34±5.98	74.13±4.87	79.03±4.38	75.14±4.63	78.20±4.17	77.74±4.49
Page.	70.92±0.00	83.70±5.17	85.49±3.84	91.40±0.83	91.94±1.87	92.78±1.59	93.11±1.00
Vert.	31.62±0.00	31.66±0.13	39.88±11.03	39.74±5.38	40.23±4.36	43.54±5.96	41.93±4.60
Card.	60.06±0.00	62.33±12.80	58.51±4.28	55.37±4.28	53.92±5.69	59.64±5.62	61.48±8.70
WPBC	56.47±0.00	56.44±0.05	54.29±0.57	54.55±1.10	55.30±0.56	54.90±0.54	55.02±0.36
Sate.	38.03±0.00	57.34±6.14	40.61±0.81	43.79±8.64	39.10±0.26	49.16±10.46	46.26±10.12
Pima	76.08±0.00	73.81±1.82	70.48±2.98	66.23±2.49	71.15±2.51	68.92±3.46	70.74±2.63
Brea.	99.53±0.00	99.30±0.17	96.63±1.04	97.80±0.70	97.96±0.24	98.21±0.38	98.09±0.59
Iono.	32.83±0.00	32.88±0.10	35.83±2.37	38.28±3.80	39.05±6.50	41.24±11.79	41.79±6.75
Spam.	60.31±0.00	56.32±2.23	46.17±4.69	50.39±4.64	49.07±6.93	52.51±3.04	53.96±3.00
Hear.	85.21±0.00	85.19±0.20	71.70±14.83	71.48±10.74	75.71±10.01	79.25±7.45	77.87±7.17
Arrh.	55.38±0.00	55.44±0.05	51.53±4.18	52.47±4.43	58.78±5.66	61.37±6.55	58.13±5.58
Park.	79.08±0.00	79.16±0.17	73.21±6.89	75.67±7.47	75.20±6.94	75.59±4.27	74.08±6.04

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	1.23±2.97	0.32±0.03	0.32±0.05	0.29±0.07	0.31±0.06	0.55±0.62
Sati.	1.89±0.00	87.92±26.34	1.80±0.04	26.73±31.17	37.33±39.71	10.17±20.69	21.46±27.82
Shut.	17.14±0.00	9.29±15.64	19.86±21.09	20.48±12.39	14.93±7.68	20.63±11.14	20.18±12.45
WBC	70.28±0.00	70.15±0.17	40.13±9.90	37.97±7.27	41.63±6.20	43.58±7.43	42.65±4.89
Thyr.	10.10±0.00	37.37±19.45	34.99±13.89	42.22±6.49	40.11±6.27	38.37±9.81	42.37±8.09
WDBC	70.66±0.00	70.78±0.36	69.72±0.89	69.55±2.44	68.79±3.58	70.02±1.98	66.82±8.43
Optd.	3.41±0.00	19.47±20.10	2.44±0.16	3.07±0.97	2.30±0.67	2.01±0.47	2.32±0.65
Wave.	2.88±0.00	3.71±0.72	3.01±0.07	3.18±0.33	3.23±0.42	3.35±0.68	3.09±0.19
Musk	1.72±0.00	89.80±25.29	28.83±21.89	46.61±23.86	64.21±25.43	88.10±11.46	76.64±19.32
Vowe.	39.78±0.00	12.48±7.91	14.69±15.73	16.23±14.62	18.89±14.77	16.61±8.94	21.03±12.24
Lymp.	64.39±0.00	64.39±0.00	43.65±16.69	48.94±18.02	29.30±10.67	36.44±16.45	45.09±17.43
Glass	2.45±0.00	2.44±0.04	6.10±2.93	8.83±3.98	9.87±4.85	9.14±4.59	10.03±4.71
Wilt	3.57±0.00	3.80±0.69	3.53±0.22	3.58±0.10	3.69±0.29	3.85±0.47	3.66±0.36
Lett.	7.42±0.00	6.85±0.76	7.75±0.36	7.50±0.07	7.44±0.42	7.65±0.24	7.75±0.50
Annt.	7.43±0.00	10.57±2.05	10.46±3.64	11.67±1.82	10.17±1.27	10.60±0.36	10.54±0.18
Wine	49.35±0.00	48.94±0.37	42.35±10.77	41.90±8.55	44.28±11.31	43.49±8.57	37.39±9.78
Stam.	15.64±0.00	15.67±0.27	25.18±11.54	26.45±9.86	26.85±9.21	26.91±9.53	29.50±6.88
Mnist	22.31±0.00	37.04±9.54	28.69±3.44	33.86±3.68	29.67±3.39	32.49±2.93	31.78±4.05
Page.	35.38±0.00	45.57±10.48	48.16±7.89	57.82±3.46	58.83±6.81	61.87±2.95	62.34±3.50
Vert.	8.56±0.00	8.56±0.01	10.34±2.28	9.77±0.92	9.70±0.72	10.25±1.02	9.95±0.77
Card.	28.82±0.00	35.98±13.98	28.38±4.49	25.98±5.33	25.89±5.59	29.65±4.10	33.51±8.25
WPBC	25.68±0.00	25.66±0.04	24.13±0.51	24.45±0.68	24.98±0.51	24.75±0.59	24.83±0.37
Sate.	24.44±0.00	47.96±9.10	26.19±0.72	30.19±9.92	25.10±0.16	39.33±15.11	36.93±14.60
Pima	61.69±0.00	59.93±1.95	50.70±5.04	47.25±2.50	51.95±3.35	50.76±4.37	50.94±3.37
Brea.	99.11±0.00	98.63±0.32	88.44±4.02	91.82±3.22	92.62±1.66	93.97±1.76	93.39±2.45
Iono.	30.87±0.00	30.88±0.05	32.18±1.47	35.14±4.09	35.35±6.42	37.97±12.31	37.35±6.51
Spam.	44.11±0.00	41.84±1.65	36.33±2.48	38.60±2.86	38.14±3.44	39.70±1.61	40.50±1.56
Hear.	81.29±0.00	81.24±0.37	65.21±16.76	64.20±13.70	69.46±11.99	73.43±10.17	72.02±8.97
Arrh.	56.00±0.00	56.07±0.03	52.38±2.95	54.04±3.73	58.48±3.73	60.96±4.97	57.53±4.43
Park.	93.37±0.00	93.40±0.05	90.90±3.43	91.89±3.37	91.60±3.33	92.08±1.68	91.21±2.86

Table A20: DTE's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	0.00±0.00	53.40±16.01	39.93±14.97	59.49±6.69	63.12±7.47	68.71±6.54
Sati.	0.00±0.00	0.00±0.00	40.50±39.16	53.32±34.38	98.64±0.25	98.97±0.21	99.04±0.18
Shut.	0.00±0.00	0.00±0.00	59.52±36.32	61.69±29.56	79.75±11.94	84.93±13.05	85.22±20.60
WBC	0.00±0.00	0.00±0.00	67.11±28.95	52.51±40.08	98.32±0.12	98.28±0.12	98.32±0.10
Thyr.	0.00±0.00	0.00±0.00	52.12±21.00	44.16±21.00	95.72±0.65	96.36±0.45	96.21±0.63
WDBC	0.00±0.00	0.00±0.00	43.25±37.95	52.63±39.11	70.28±4.57	64.59±3.52	66.26±2.95
Optd.	0.00±0.00	0.00±0.00	43.18±21.77	41.45±18.19	38.71±9.31	37.12±4.32	41.78±8.13
Wave.	0.00±0.00	0.00±0.00	50.56±19.67	56.79±15.50	64.64±2.21	67.69±3.51	64.27±2.76
Musk	0.00±0.00	0.00±0.00	40.42±30.85	35.75±32.85	100.00±0.00	99.96±0.07	99.96±0.07
Vowe.	0.00±0.00	0.00±0.00	47.84±13.32	39.89±13.91	70.67±2.22	76.25±3.04	74.50±2.23
Lymp.	0.00±0.00	0.00±0.00	51.46±31.29	42.08±30.23	83.69±1.86	83.51±1.59	83.25±1.54
Glass	0.00±0.00	0.00±0.00	61.56±21.67	59.54±22.47	69.37±4.87	67.70±6.76	65.96±4.70
Wilt	0.00±0.00	0.00±0.00	47.95±13.35	51.11±13.98	48.98±4.65	49.55±4.02	52.23±2.42
Lett.	0.00±0.00	0.00±0.00	46.95±6.89	51.33±4.28	53.52±2.48	57.23±1.20	55.69±2.39
Annt.	0.00±0.00	0.00±0.00	50.11±18.96	48.84±12.53	65.41±8.25	64.13±7.02	64.89±7.97
Wine	0.00±0.00	0.00±0.00	32.24±31.28	32.04±34.86	6.58±8.61	32.90±17.41	21.29±21.42
Stam.	0.00±0.00	0.00±0.00	40.33±28.90	58.27±17.52	80.72±9.31	81.57±5.24	80.45±7.08
Mnist	0.00±0.00	0.00±0.00	41.96±15.98	44.53±15.29	61.29±6.17	58.63±3.86	62.95±3.59
Page.	0.00±0.00	0.00±0.00	51.67±16.12	50.86±17.39	68.67±17.40	64.95±11.14	68.27±15.18
Vert.	0.00±0.00	0.00±0.00	46.10±14.48	59.16±19.03	46.23±5.09	49.09±4.45	49.24±3.98
Card.	0.00±0.00	0.00±0.00	43.28±12.65	57.80±6.13	68.69±7.67	69.47±6.07	67.22±6.76
WPBC	0.00±0.00	0.00±0.00	50.02±8.27	54.96±6.52	41.56±1.38	41.27±1.44	40.31±1.81
Sate.	0.00±0.00	0.00±0.00	56.35±19.17	41.80±16.78	74.05±1.20	75.00±1.21	74.52±1.20
Pima	0.00±0.00	0.00±0.00	47.99±15.56	45.67±11.60	50.26±2.51	57.86±2.53	55.11±4.21
Brea.	0.00±0.00	0.00±0.00	46.62±33.58	44.25±38.09	69.26±7.19	79.27±5.46	78.70±6.24
Iono.	0.00±0.00	0.00±0.00	48.92±10.67	49.15±14.71	87.68±0.75	87.51±1.28	86.75±1.51
Spam.	0.00±0.00	0.00±0.00	50.00±11.04	53.33±13.69	38.46±6.47	36.23±9.60	31.67±5.77
Hear.	0.00±0.00	0.00±0.00	42.89±17.25	53.87±14.44	40.86±6.27	41.64±7.21	43.73±6.47
Arrh.	0.00±0.00	0.00±0.00	50.33±7.53	48.03±6.87	61.20±4.54	59.95±4.57	59.20±3.96
Park.	0.00±0.00	0.00±0.00	59.14±22.20	55.07±24.28	21.91±5.93	25.41±4.55	27.02±6.40

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	0.00±0.00	0.26±0.18	0.17±0.07	0.24±0.04	0.27±0.06	0.33±0.08
Sati.	0.00±0.00	0.00±0.00	11.62±16.50	24.42±35.68	76.92±5.96	82.22±6.85	85.27±6.06
Shut.	0.00±0.00	0.00±0.00	28.23±40.06	19.18±27.64	11.25±4.18	14.29±5.39	16.58±5.43
WBC	0.00±0.00	0.00±0.00	24.01±22.86	32.18±27.40	65.15±3.69	66.12±1.33	65.92±1.97
Thyr.	0.00±0.00	0.00±0.00	8.32±5.89	12.64±18.59	39.42±3.10	41.62±2.17	41.60±2.83
WDBC	0.00±0.00	0.00±0.00	22.20±31.58	25.12±31.39	49.50±1.96	45.04±4.00	48.01±2.63
Optd.	0.00±0.00	0.00±0.00	2.75±1.08	2.59±1.21	2.19±0.34	2.07±0.15	2.32±0.40
Wave.	0.00±0.00	0.00±0.00	3.96±2.23	4.89±2.81	4.80±0.30	5.25±0.61	4.62±0.44
Musk	0.00±0.00	0.00±0.00	11.14±13.88	17.23±29.42	100.00±0.00	98.87±1.76	99.02±1.80
Vowe.	0.00±0.00	0.00±0.00	3.59±1.01	3.63±2.95	15.14±2.28	16.65±2.31	16.02±3.84
Lymp.	0.00±0.00	0.00±0.00	24.70±28.38	18.66±25.23	66.35±0.89	66.27±1.13	66.11±1.14
Glass	0.00±0.00	0.00±0.00	14.34±13.56	8.30±7.22	7.28±0.67	7.51±0.99	7.13±0.67
Wilt	0.00±0.00	0.00±0.00	5.23±1.97	5.39±1.51	5.00±0.47	5.04±0.42	5.31±0.28
Lett.	0.00±0.00	0.00±0.00	6.78±1.74	7.55±2.34	8.40±0.76	9.40±0.36	8.83±0.65
Annt.	0.00±0.00	0.00±0.00	12.43±11.61	7.98±3.18	18.23±8.22	18.36±7.51	19.52±8.21
Wine	0.00±0.00	0.00±0.00	13.85±22.88	11.74±13.97	4.18±0.35	6.09±1.84	5.54±2.98
Stam.	0.00±0.00	0.00±0.00	16.05±16.05	18.63±12.73	24.75±6.53	24.30±4.32	24.46±5.77
Mnist	0.00±0.00	0.00±0.00	12.86±8.25	13.19±5.46	16.60±3.49	15.60±3.06	19.02±2.37
Page.	0.00±0.00	0.00±0.00	29.16±12.93	27.84±13.68	42.48±13.28	40.44±12.65	44.12±14.89
Vert.	0.00±0.00	0.00±0.00	12.46±4.39	17.29±7.45	10.71±0.96	11.28±0.97	11.33±0.90
Card.	0.00±0.00	0.00±0.00	23.96±7.38	30.77±7.56	43.61±4.43	43.95±4.06	42.28±4.38
WPBC	0.00±0.00	0.00±0.00	24.06±4.41	28.08±5.69	19.99±0.47	20.02±0.45	19.66±0.64
Sate.	0.00±0.00	0.00±0.00	43.96±20.39	32.48±12.39	66.66±2.95	69.27±2.22	68.66±1.67
Pima	0.00±0.00	0.00±0.00	37.31±12.29	34.94±7.62	39.69±1.55	43.60±1.53	42.18±2.43
Brea.	0.00±0.00	0.00±0.00	52.45±27.87	50.24±31.22	70.27±5.43	76.83±4.62	76.79±4.49
Iono.	0.00±0.00	0.00±0.00	42.78±9.15	48.00±13.38	82.84±0.76	82.70±1.22	82.14±1.38
Spam.	0.00±0.00	0.00±0.00	41.29±8.01	44.91±11.51	33.12±2.81	32.72±5.05	30.33±2.09
Hear.	0.00±0.00	0.00±0.00	43.60±14.10	50.52±11.63	43.80±4.27	44.13±5.05	45.67±4.57
Arrh.	0.00±0.00	0.00±0.00	51.56±5.81	50.06±5.67	63.50±3.86	62.11±4.11	61.40±4.37
Park.	0.00±0.00	0.00±0.00	81.78±11.70	79.96±12.57	64.60±3.61	67.32±2.93	68.28±3.89

Table A21: VAE's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	62.38±6.88	63.36±5.98	57.34±3.65	57.13±3.74	57.12±3.73	57.12±3.73
Sati.	67.11±0.00	64.17±4.61	64.23±4.04	95.05±0.74	95.20±0.80	95.19±0.80	95.19±0.80
Shut.	86.93±0.00	67.96±13.09	66.23±13.09	64.11±13.54	63.40±13.32	63.38±13.30	63.39±13.29
WBC	98.65±0.00	90.32±8.43	90.31±7.95	97.72±1.47	97.47±1.95	97.47±1.94	97.47±1.94
Thyr.	45.04±0.00	54.82±11.73	53.76±11.31	60.14±12.18	59.83±11.47	59.81±11.45	59.81±11.45
WDBC	97.68±0.00	94.06±2.17	94.37±1.45	90.83±2.32	90.84±2.43	90.84±2.43	90.84±2.43
Optd.	59.10±0.00	48.93±2.44	49.58±2.49	48.36±3.24	48.13±3.54	48.16±3.52	48.16±3.51
Wave.	51.22±0.00	48.30±4.80	48.57±3.85	52.60±4.82	53.20±4.68	53.20±4.70	53.20±4.70
Musk	11.94±0.00	41.67±3.56	34.19±4.99	97.18±0.64	99.34±0.19	99.33±0.20	99.33±0.20
Vowe.	90.15±0.00	74.66±9.92	75.06±10.17	66.59±7.91	66.27±7.04	66.27±7.05	66.27±7.04
Lymp.	70.77±23.33	81.15±11.57	80.82±11.99	82.73±9.06	82.55±9.55	82.53±9.55	82.53±9.55
Glass	20.22±0.00	43.15±10.37	41.70±10.88	45.22±15.26	44.62±15.07	44.60±15.03	44.61±15.03
Wilt	39.96±10.81	42.41±4.39	42.59±4.82	39.54±6.76	39.78±6.82	39.78±6.82	39.78±6.82
Lett.	56.33±0.00	53.93±2.05	53.83±2.20	51.81±2.56	51.64±2.73	51.64±2.73	51.64±2.73
Annt.	44.18±0.00	49.72±2.67	49.70±2.64	51.43±1.85	51.22±1.94	51.23±1.93	51.23±1.93
Wine	95.80±0.00	91.25±3.00	91.76±2.74	85.19±6.54	84.75±7.15	84.78±7.12	84.78±7.12
Stam.	66.81±0.00	61.43±10.59	61.03±10.59	56.83±10.77	56.67±9.90	56.68±9.93	56.68±9.93
Mnist	58.28±0.00	50.66±1.19	50.73±1.27	61.12±1.04	68.44±1.27	68.41±1.26	68.41±1.26
Page.	70.92±0.00	55.04±2.95	54.72±2.82	57.82±2.91	57.14±2.59	57.12±2.58	57.12±2.58
Vert.	31.62±0.00	35.19±8.13	34.88±7.93	34.43±7.24	34.62±7.40	34.63±7.38	34.63±7.38
Card.	60.06±0.00	52.94±3.77	53.06±3.87	61.16±3.54	60.88±3.78	60.88±3.80	60.88±3.80
WPBC	56.47±0.00	54.89±2.75	55.36±2.44	52.86±3.15	52.63±3.27	52.64±3.27	52.63±3.27
Sate.	38.03±0.00	37.45±1.61	37.37±1.39	58.63±0.62	59.23±0.64	59.23±0.64	59.23±0.64
Pima	76.08±0.00	71.82±4.49	72.00±4.11	70.36±3.35	69.99±3.60	69.99±3.60	69.99±3.59
Brea.	99.53±0.00	96.65±5.01	96.85±4.49	98.35±0.39	98.32±0.53	98.32±0.53	98.32±0.53
Iono.	32.83±0.00	33.80±1.10	33.53±1.07	68.77±2.04	69.42±2.20	69.41±2.21	69.42±2.21
Spam.	60.31±0.00	49.91±1.00	49.80±0.96	51.26±1.01	51.99±0.83	51.99±0.82	51.99±0.82
Hear.	85.21±0.00	75.89±5.42	76.18±5.42	68.64±5.63	68.85±5.55	68.87±5.56	68.87±5.56
Arrh.	55.38±0.00	52.04±2.38	54.38±3.04	55.17±2.27	56.59±2.35	56.60±2.37	56.60±2.36
Park.	79.08±0.00	73.32±3.94	72.45±4.19	48.53±3.69	47.95±4.26	47.97±4.26	47.97±4.27

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.31±0.08	0.32±0.08	0.31±0.08	0.30±0.07	0.30±0.07	0.30±0.07
Sati.	1.89±0.00	1.70±0.36	1.69±0.34	36.61±11.84	37.13±12.94	37.06±12.96	37.05±12.96
Shut.	17.14±0.00	4.89±3.94	4.45±3.19	5.42±4.02	5.50±3.95	5.49±3.94	5.50±3.95
WBC	70.28±0.00	54.71±17.69	54.96±17.53	64.90±6.23	64.81±6.82	64.91±6.82	64.91±6.82
Thyr.	10.10±0.00	8.65±5.31	8.76±5.19	12.93±6.07	12.70±5.97	12.70±5.98	12.70±5.98
WDBC	70.66±0.00	58.06±8.97	60.08±5.16	57.71±4.25	57.62±4.02	57.62±4.02	57.62±4.02
Optd.	3.41±0.00	2.85±0.23	2.87±0.24	2.65±0.22	2.59±0.19	2.59±0.19	2.59±0.19
Wave.	2.88±0.00	2.80±0.33	2.78±0.24	3.23±0.51	3.27±0.51	3.27±0.51	3.27±0.51
Musk	1.72±0.00	2.60±0.21	2.25±0.23	52.87±7.37	82.16±3.77	82.03±3.81	82.02±3.81
Vowe.	39.78±0.00	13.51±7.37	14.71±8.88	9.73±4.38	9.65±4.23	9.63±4.22	9.63±4.22
Lymp.	47.58±27.67	54.49±23.45	54.79±23.28	60.28±13.87	60.33±13.83	59.93±13.75	59.93±13.75
Glass	2.45±0.00	4.87±3.78	4.73±3.85	4.51±1.95	4.32±1.72	4.31±1.71	4.31±1.71
Wilt	4.21±0.83	4.51±0.66	4.48±0.58	4.11±0.52	4.12±0.52	4.12±0.52	4.12±0.52
Lett.	7.42±0.00	6.87±0.42	6.88±0.45	6.66±0.59	6.63±0.62	6.63±0.62	6.63±0.62
Annt.	7.43±0.00	7.48±0.51	7.46±0.54	7.90±0.42	7.89±0.49	7.89±0.48	7.89±0.48
Wine	49.35±0.00	36.06±8.97	36.81±8.22	31.32±11.11	31.17±11.53	31.22±11.54	31.22±11.54
Stam.	15.64±0.00	14.56±7.31	14.37±6.89	13.62±3.95	13.41±3.44	13.43±3.48	13.44±3.48
Mnist	22.31±0.00	9.47±0.38	9.55±0.42	16.88±0.97	24.06±1.07	24.07±1.08	24.07±1.08
Page.	35.38±0.00	12.12±2.06	12.05±1.91	16.20±2.61	15.90±2.53	15.89±2.52	15.89±2.52
Vert.	8.56±0.00	9.14±1.02	9.08±0.93	8.99±0.87	9.03±0.90	9.03±0.90	9.03±0.90
Card.	28.82±0.00	24.70±1.62	24.58±1.99	32.10±4.08	31.74±4.16	31.75±4.17	31.75±4.17
WPBC	25.68±0.00	25.38±1.19	25.46±1.07	24.06±1.92	24.04±2.03	24.05±2.04	24.04±2.04
Sate.	24.44±0.00	24.28±0.55	24.24±0.46	48.57±2.38	49.57±2.47	49.55±2.48	49.55±2.48
Pima	61.69±0.00	56.08±5.80	56.11±5.59	55.14±2.38	54.98±2.52	54.98±2.51	54.98±2.51
Brea.	99.11±0.00	94.43±8.20	94.81±7.26	97.43±0.66	97.36±0.81	97.36±0.81	97.36±0.81
Iono.	30.87±0.00	31.05±0.76	31.01±0.71	58.99±4.71	59.82±4.73	59.83±4.75	59.83±4.75
Spam.	44.11±0.00	39.84±0.61	39.90±0.66	39.43±0.59	39.63±0.48	39.63±0.47	39.63±0.47
Hear.	81.29±0.00	68.88±5.96	69.29±6.30	62.57±6.12	62.78±6.34	62.81±6.33	62.80±6.33
Arrh.	56.00±0.00	48.97±1.71	51.55±2.11	49.43±2.95	50.33±2.73	50.34±2.74	50.35±2.74
Park.	93.37±0.00	89.57±2.18	89.23±2.20	77.90±2.00	77.48±2.48	77.49±2.48	77.49±2.48

Table A22: β-VAE's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	62.38±6.88	63.36±5.98	57.38±3.62	57.15±3.72	57.14±3.72	57.14±3.72
Sati.	67.11±0.00	64.17±4.61	64.23±4.04	95.05±0.73	95.19±0.81	95.19±0.81	95.18±0.81
Shut.	86.93±0.00	67.96±13.09	66.23±13.09	64.20±13.53	63.39±13.24	63.39±13.22	63.39±13.21
WBC	98.65±0.00	90.32±8.43	90.31±7.95	97.73±1.47	97.48±1.95	97.48±1.94	97.48±1.94
Thyr.	45.04±0.00	54.82±11.73	53.76±11.31	60.14±12.18	59.83±11.47	59.81±11.45	59.81±11.45
WDBC	97.68±0.00	94.06±2.17	94.37±1.45	91.39±2.00	91.39±2.10	91.40±2.08	91.40±2.09
Optd.	59.10±0.00	48.93±2.44	49.58±2.49	48.43±3.27	48.14±3.49	48.15±3.47	48.15±3.47
Wave.	51.22±0.00	48.30±4.80	48.57±3.85	52.61±4.90	53.14±4.75	53.14±4.76	53.14±4.76
Musk	11.94±0.00	41.67±3.56	34.19±4.99	97.19±0.64	99.33±0.19	99.33±0.19	99.33±0.19
Vowe.	90.15±0.00	74.66±9.92	75.06±10.17	66.38±7.50	66.27±7.03	66.28±7.04	66.28±7.04
Lymp.	70.77±23.33	81.15±11.57	80.82±11.99	82.78±9.07	82.58±9.62	82.55±9.61	82.55±9.61
Glass	20.22±0.00	43.15±10.37	41.70±10.88	45.71±14.84	45.58±14.11	45.56±14.13	45.56±14.13
Wilt	39.96±10.81	42.41±4.39	42.59±4.82	39.54±6.76	39.78±6.82	39.78±6.82	39.78±6.82
Lett.	56.33±0.00	53.93±2.05	53.83±2.20	51.83±2.51	51.67±2.63	51.67±2.63	51.67±2.63
Annt.	44.18±0.00	49.72±2.67	49.70±2.64	51.42±1.85	51.22±1.94	51.23±1.93	51.23±1.93
Wine	95.80±0.00	91.25±3.00	91.76±2.74	84.28±6.38	83.77±6.86	83.76±6.85	83.77±6.86
Stam.	66.81±0.00	61.43±10.59	61.03±10.59	56.75±11.08	56.73±10.18	56.73±10.19	56.74±10.20
Mnist	58.28±0.00	50.66±1.19	50.73±1.27	61.12±1.06	68.44±1.29	68.41±1.28	68.41±1.27
Page.	70.92±0.00	55.04±2.95	54.72±2.82	57.83±2.91	57.15±2.60	57.13±2.58	57.13±2.59
Vert.	31.62±0.00	35.19±8.13	34.88±7.93	34.49±7.17	34.68±7.32	34.69±7.30	34.69±7.30
Card.	60.06±0.00	52.94±3.77	53.06±3.87	61.16±3.59	60.86±3.76	60.87±3.77	60.87±3.77
WPBC	56.47±0.00	54.89±2.75	55.36±2.44	52.48±3.50	52.37±3.33	52.39±3.35	52.36±3.32
Sate.	38.03±0.00	37.45±1.61	37.37±1.39	58.63±0.63	59.22±0.63	59.22±0.63	59.22±0.63
Pima	76.08±0.00	71.82±4.49	72.00±4.11	70.28±3.32	69.96±3.60	69.95±3.59	69.95±3.59
Brea.	99.53±0.00	96.65±5.01	96.85±4.49	98.35±0.39	98.32±0.52	98.32±0.52	98.32±0.52
Iono.	32.83±0.00	33.80±1.10	33.53±1.07	68.74±1.80	69.44±1.82	69.45±1.81	69.44±1.81
Spam.	60.31±0.00	49.91±1.00	49.80±0.96	51.28±1.01	51.98±0.82	51.99±0.82	51.99±0.82
Hear.	85.21±0.00	75.89±5.42	76.18±5.42	68.44±5.75	68.64±5.75	68.68±5.74	68.68±5.74
Arrh.	55.38±0.00	52.04±2.38	54.38±3.04	55.17±2.08	56.61±2.25	56.60±2.28	56.67±2.26
Park.	79.08±0.00	73.32±3.94	72.45±4.19	48.63±3.62	48.24±3.97	48.25±3.96	48.24±3.95

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.31±0.08	0.32±0.08	0.31±0.08	0.30±0.07	0.30±0.07	0.30±0.07
Sati.	1.89±0.00	1.70±0.36	1.69±0.34	36.53±11.74	37.21±12.99	37.11±13.03	37.11±13.03
Shut.	17.14±0.00	4.89±3.94	4.45±3.19	5.48±4.00	5.51±3.93	5.51±3.93	5.51±3.93
WBC	70.28±0.00	54.71±17.69	54.96±17.53	65.04±5.98	64.95±6.66	65.04±6.66	65.04±6.66
Thyr.	10.10±0.00	8.65±5.31	8.76±5.19	12.93±6.07	12.70±5.97	12.70±5.98	12.70±5.98
WDBC	70.66±0.00	58.06±8.97	60.08±5.16	57.68±4.13	57.65±3.97	57.74±4.01	57.73±4.01
Optd.	3.41±0.00	2.85±0.23	2.87±0.24	2.65±0.22	2.59±0.19	2.59±0.19	2.59±0.19
Wave.	2.88±0.00	2.80±0.33	2.78±0.24	3.23±0.52	3.28±0.53	3.28±0.53	3.28±0.53
Musk	1.72±0.00	2.60±0.21	2.25±0.23	52.95±7.37	82.13±3.74	82.06±3.78	82.07±3.78
Vowe.	39.78±0.00	13.51±7.37	14.71±8.88	9.78±4.51	9.50±4.23	9.46±4.27	9.61±4.26
Lymp.	47.58±27.67	54.49±23.45	54.79±23.28	60.30±13.86	60.44±13.89	60.04±13.81	60.04±13.81
Glass	2.45±0.00	4.87±3.78	4.73±3.85	4.57±2.00	4.40±1.73	4.41±1.76	4.41±1.76
Wilt	4.21±0.83	4.51±0.66	4.48±0.58	4.11±0.52	4.12±0.52	4.12±0.52	4.12±0.52
Lett.	7.42±0.00	6.87±0.42	6.88±0.45	6.65±0.56	6.62±0.56	6.62±0.56	6.62±0.56
Annt.	7.43±0.00	7.48±0.51	7.46±0.54	7.90±0.43	7.90±0.49	7.90±0.49	7.90±0.49
Wine	49.35±0.00	36.06±8.97	36.81±8.22	31.12±11.80	32.53±13.91	32.52±13.94	32.54±13.94
Stam.	15.64±0.00	14.56±7.31	14.37±6.89	13.78±4.10	13.65±3.63	13.66±3.63	13.67±3.65
Mnist	22.31±0.00	9.47±0.38	9.55±0.42	16.88±0.98	24.06±1.09	24.07±1.09	24.07±1.09
Page.	35.38±0.00	12.12±2.06	12.05±1.91	16.21±2.63	15.93±2.55	15.91±2.54	15.91±2.54
Vert.	8.56±0.00	9.14±1.02	9.08±0.93	8.99±0.86	9.03±0.89	9.03±0.89	9.03±0.89
Card.	28.82±0.00	24.70±1.62	24.58±1.99	32.11±4.12	31.73±4.16	31.73±4.17	31.73±4.16
WPBC	25.68±0.00	25.38±1.19	25.46±1.07	24.00±1.94	23.95±1.83	23.96±1.85	23.94±1.83
Sate.	24.44±0.00	24.28±0.55	24.24±0.46	48.56±2.39	49.57±2.47	49.55±2.47	49.55±2.47
Pima	61.69±0.00	56.08±5.80	56.11±5.59	55.02±2.28	54.89±2.43	54.88±2.42	54.89±2.42
Brea.	99.11±0.00	94.43±8.20	94.81±7.26	97.43±0.63	97.36±0.79	97.37±0.78	97.37±0.78
Iono.	30.87±0.00	31.05±0.76	31.01±0.71	58.87±4.43	59.60±4.31	59.62±4.29	59.60±4.30
Spam.	44.11±0.00	39.84±0.61	39.90±0.66	39.44±0.59	39.63±0.47	39.63±0.47	39.63±0.47
Hear.	81.29±0.00	68.88±5.96	69.29±6.30	62.37±6.10	62.59±6.20	62.63±6.19	62.63±6.19
Arrh.	56.00±0.00	48.97±1.71	51.55±2.11	49.50±2.81	50.32±2.64	50.30±2.66	50.33±2.64
Park.	93.37±0.00	89.57±2.18	89.23±2.20	77.83±1.85	77.61±2.25	77.63±2.22	77.61±2.21

Table A23: PAE's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	66.28±9.84	65.78±10.75	76.18±13.14	78.26±14.20	76.08±13.43	81.42±13.19
Sati.	67.11±0.00	67.34±6.32	67.27±6.08	98.67±2.08	98.53±2.53	99.01±1.49	98.98±1.31
Shut.	86.93±0.00	66.99±29.81	68.68±29.46	90.82±2.27	91.56±2.48	93.17±1.69	92.63±1.87
WBC	98.65±0.00	80.73±24.65	81.92±24.34	98.47±0.56	98.29±0.40	98.12±0.67	98.43±0.05
Thyr.	48.71±34.28	59.44±38.06	58.69±37.89	93.88±6.84	95.25±4.68	92.83±10.81	96.48±0.88
WDBC	97.68±0.00	97.42±0.34	97.46±0.31	83.40±14.36	91.93±3.30	90.83±6.44	88.36±7.85
Optd.	59.10±0.00	63.07±17.15	61.43±20.58	40.06±11.99	55.47±12.20	60.00±11.39	55.78±5.94
Wave.	51.22±0.00	47.90±6.61	49.11±6.10	61.91±14.63	53.80±8.64	59.05±12.79	54.10±11.94
Musk	11.94±0.00	16.11±6.61	15.51±5.38	82.39±29.70	79.61±20.30	93.98±6.83	89.67±16.00
Vowe.	90.15±0.00	77.98±9.61	78.07±8.67	72.81±7.82	71.61±7.91	72.73±11.06	77.19±7.92
Lymp.	77.69±9.65	68.35±23.33	68.54±22.12	85.39±4.12	85.53±4.60	78.69±17.22	84.80±3.15
Glass	20.22±0.00	33.71±15.23	33.63±14.07	75.25±5.40	73.86±5.71	71.96±5.82	72.56±4.84
Wilt	49.10±13.01	50.23±12.60	50.36±12.89	33.64±2.44	34.89±3.28	34.79±2.47	34.39±2.26
Lett.	56.33±0.00	56.42±1.69	56.45±1.78	73.94±3.44	77.94±2.99	75.43±3.55	74.04±4.87
Annt.	44.18±0.00	43.65±14.88	44.05±13.40	61.60±3.93	63.92±2.29	63.05±5.70	63.16±2.87
Wine	95.80±0.00	93.66±2.93	93.94±2.66	36.48±36.42	39.92±37.33	45.09±34.12	24.81±31.01
Stam.	66.81±0.00	53.56±19.84	52.82±19.89	88.84±2.85	87.77±7.40	89.33±2.48	85.15±12.18
Mnist	58.28±0.00	55.71±15.98	57.54±16.78	84.98±6.68	85.18±1.91	85.46±1.04	84.33±2.80
Page.	70.92±0.00	67.06±9.63	65.32±10.66	89.10±3.33	89.73±0.80	89.50±1.22	89.62±1.26
Vert.	46.84±18.81	45.25±15.52	44.42±15.21	49.75±11.95	46.97±8.92	42.32±8.96	41.14±7.11
Card.	60.06±0.00	60.66±10.81	60.68±10.25	45.08±1.95	44.63±1.07	48.58±9.23	48.33±8.75
WPBC	56.47±0.00	56.60±1.01	56.73±1.12	40.42±2.06	44.37±4.24	47.50±4.49	46.34±3.31
Sate.	38.03±0.00	38.17±2.16	38.13±2.07	76.63±2.68	76.95±5.76	74.98±4.71	78.77±2.07
Pima	76.08±0.00	71.63±5.65	71.85±5.19	55.11±4.82	60.41±4.63	62.03±3.90	65.87±2.63
Brea.	99.53±0.00	90.35±16.31	91.00±16.18	94.43±4.81	96.65±1.30	96.27±1.30	96.45±1.75
Iono.	32.83±0.00	33.20±1.55	33.23±1.36	94.87±3.15	96.51±2.48	94.22±3.75	95.61±3.31
Spam.	60.31±0.00	58.12±11.24	58.47±10.90	51.29±8.36	54.80±1.91	53.96±1.79	55.99±1.71
Hear.	85.21±0.00	79.42±4.26	79.72±4.21	37.71±17.07	38.42±15.54	49.53±15.96	48.16±14.93
Arrh.	55.38±0.00	55.56±0.53	55.54±0.41	74.04±1.33	74.12±2.67	73.85±1.16	72.88±0.80
Park.	79.08±0.00	74.82±6.81	75.40±6.37	40.24±19.71	67.49±13.79	56.79±19.05	68.08±11.92

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.89±1.65	0.90±1.68	0.61±0.32	0.59±0.22	0.52±0.22	0.73±0.24
Sati.	1.89±0.00	3.12±2.46	2.80±1.84	50.34±23.79	60.85±29.75	65.91±23.05	62.18±22.78
Shut.	17.14±0.00	12.88±10.86	12.79±8.86	12.65±2.44	13.30±3.37	15.00±2.34	14.43±2.62
WBC	70.28±0.00	51.80±16.77	52.13±16.02	61.43±8.71	61.76±8.20	53.79±12.79	60.41±7.69
Thyr.	16.34±20.45	27.98±24.68	26.03±23.38	37.59±11.55	38.19±10.91	38.75±12.67	39.05±5.65
WDBC	70.66±0.00	69.67±3.53	69.51±3.56	21.22±11.77	30.09±10.84	26.35±9.55	25.88±8.76
Optd.	3.41±0.00	4.74±2.76	4.57±2.34	2.27±0.52	3.11±0.82	3.54±1.16	2.99±0.47
Wave.	2.88±0.00	2.75±0.48	2.82±0.45	5.99±5.13	3.54±1.23	7.41±8.66	7.12±10.38
Musk	1.72±0.00	1.99±0.69	1.95±0.46	71.27±43.90	37.63±39.49	48.73±32.75	54.78±38.15
Vowe.	39.78±0.00	16.85±12.59	16.64±10.95	12.54±6.68	11.43±5.02	13.68±8.89	16.61±7.94
Lymp.	54.53±19.30	42.63±23.17	41.94±25.34	67.42±2.98	64.49±9.79	60.82±19.50	67.91±3.43
Glass	2.45±0.00	3.26±0.86	3.19±0.72	8.89±0.77	8.86±1.53	8.30±0.71	8.40±0.73
Wilt	5.22±1.66	5.22±1.52	5.27±1.56	3.65±0.15	3.73±0.20	3.72±0.16	3.70±0.13
Lett.	7.42±0.00	7.63±0.43	7.67±0.46	18.04±5.39	21.26±4.33	18.74±5.32	16.62±2.90
Annt.	7.43±0.00	7.83±3.51	7.67±3.30	11.26±0.97	11.14±0.56	10.81±1.22	10.93±0.82
Wine	49.35±0.00	46.18±14.85	47.20±14.45	10.54±7.97	11.56±8.34	15.16±14.62	8.18±7.89
Stam.	15.64±0.00	15.44±7.97	15.20±7.73	31.72±3.59	31.54±5.83	31.82±2.87	30.41±8.09
Mnist	22.31±0.00	21.76±7.47	22.21±7.35	38.75±5.53	41.08±1.55	39.95±1.80	40.21±2.60
Page.	35.38±0.00	38.62±13.84	37.24±14.38	49.89±3.65	51.98±2.19	51.71±2.76	52.21±2.06
Vert.	12.79±5.18	12.00±5.28	12.07±6.21	12.00±2.57	11.02±1.74	10.13±1.50	9.86±1.21
Card.	28.82±0.00	32.38±9.29	31.78±8.57	32.86±1.04	32.85±1.77	34.50±4.54	34.51±4.03
WPBC	25.68±0.00	26.03±0.99	26.17±1.07	19.38±0.58	21.13±1.49	22.06±1.77	21.42±1.02
Sate.	24.44±0.00	24.82±1.23	24.74±1.05	68.39±2.86	68.55±8.13	65.49±5.90	71.43±3.73
Pima	61.69±0.00	57.39±4.96	57.56±4.70	42.32±2.90	45.61±2.42	46.29±2.31	48.15±1.19
Brea.	99.11±0.00	90.64±14.03	91.18±13.84	92.06±4.30	93.20±1.80	94.47±1.54	90.78±4.67
Iono.	30.87±0.00	31.16±0.36	31.17±0.36	92.13±5.21	94.47±4.03	90.97±5.64	93.12±4.83
Spam.	44.11±0.00	45.54±7.32	45.48±7.48	39.20±3.70	40.29±1.47	40.58±1.42	41.55±1.57
Hear.	81.29±0.00	73.99±5.35	74.34±5.51	41.37±10.84	41.92±9.51	48.91±9.69	47.88±8.86
Arrh.	56.00±0.00	56.19±0.44	56.13±0.37	72.77±1.44	72.39±2.81	71.73±1.07	70.91±0.75
Park.	93.37±0.00	91.41±2.88	91.64±2.62	73.49±9.44	86.17±6.04	81.42±8.86	86.99±5.32

Table A24: U-DRL's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	60.30±14.54	59.29±16.44	63.57±12.53	55.89±8.10	53.89±7.65	46.25±10.83
Sati.	0.00±0.00	95.12±3.52	91.13±6.06	43.06±4.74	41.96±5.69	41.62±5.49	41.20±5.67
Shut.	0.00±0.00	80.85±17.03	89.17±11.37	91.56±3.85	94.39±3.93	96.50±1.80	96.13±2.23
WBC	0.00±0.00	98.59±0.18	95.31±0.88	95.00±1.53	95.08±1.53	94.09±1.99	94.24±1.45
Thyr.	0.00±0.00	81.09±13.35	88.82±3.43	95.54±3.18	93.99±3.13	91.89±1.63	93.64±2.42
WDBC	0.00±0.00	97.29±0.90	88.60±3.59	89.54±2.38	90.31±1.29	88.50±1.55	90.11±2.43
Optd.	0.00±0.00	66.40±20.48	60.31±22.32	46.24±5.60	44.76±5.92	44.64±5.11	45.31±4.34
Wave.	0.00±0.00	53.17±13.86	58.53±6.56	57.03±3.80	52.38±3.46	54.34±2.43	53.39±2.02
Musk	0.00±0.00	18.90±30.70	92.87±18.46	99.75±0.74	99.15±1.27	99.17±1.20	99.92±0.20
Vowe.	0.00±0.00	80.61±13.11	71.37±6.66	82.31±5.66	89.41±2.75	88.23±3.94	88.74±2.52
Lymp.	0.00±0.00	73.99±2.60	93.32±2.34	91.74±2.63	90.43±2.54	91.30±2.58	90.82±2.24
Glass	0.00±0.00	24.17±15.30	72.24±5.96	76.95±4.95	75.99±6.77	78.42±6.23	75.58±6.08
Wilt	0.00±0.00	27.63±5.09	39.62±6.99	47.25±3.41	47.89±5.78	40.87±4.89	43.84±3.08
Lett.	0.00±0.00	56.70±2.03	43.88±5.59	47.16±3.91	51.88±5.40	52.48±2.45	52.89±2.96
Annt.	0.00±0.00	55.74±5.17	56.52±3.08	57.68±1.71	55.45±0.58	54.84±0.83	55.95±1.99
Wine	0.00±0.00	90.87±4.77	75.32±11.74	76.58±8.65	68.77±7.51	77.47±8.05	71.16±8.53
Stam.	0.00±0.00	70.95±10.30	81.17±10.41	79.11±8.44	81.60±4.86	78.25±4.81	77.17±2.75
Mnist	0.00±0.00	65.39±10.89	75.15±5.00	72.22±7.30	58.55±8.96	57.14±3.46	59.22±7.38
Page.	0.00±0.00	81.47±7.84	83.31±3.22	86.11±2.86	86.71±3.04	85.45±3.95	85.09±4.24
Vert.	0.00±0.00	32.57±3.93	38.82±4.13	34.56±3.80	32.43±2.61	32.57±2.11	32.60±2.45
Card.	0.00±0.00	61.37±10.52	56.69±6.12	56.95±4.85	53.64±1.67	53.51±3.70	50.58±1.34
WPBC	0.00±0.00	56.46±1.81	48.78±5.59	45.84±2.67	44.53±1.44	43.88±1.94	42.94±1.71
Sate.	0.00±0.00	52.80±3.52	47.18±6.84	46.15±3.99	56.84±5.98	56.41±6.31	60.56±7.29
Pima	0.00±0.00	74.41±1.59	62.50±2.93	56.99±1.81	53.75±1.05	53.24±1.01	53.22±1.12
Brea.	0.00±0.00	99.48±0.05	31.47±2.83	35.13±1.95	33.23±2.52	34.93±2.40	33.43±2.90
Iono.	0.00±0.00	60.15±6.53	73.79±7.68	89.35±3.97	89.84±2.70	89.05±4.17	89.95±1.07
Spam.	0.00±0.00	55.61±6.39	38.37±4.56	45.73±3.56	49.58±3.94	51.63±2.27	52.21±4.04
Hear.	0.00±0.00	79.62±4.09	57.05±9.70	51.26±4.22	53.12±2.16	50.76±3.60	51.97±2.43
Arrh.	0.00±0.00	53.64±7.46	50.52±1.69	55.24±5.41	65.13±2.00	64.81±1.69	65.23±1.69
Park.	0.00±0.00	73.97±6.42	47.46±8.56	40.65±5.21	38.34±5.92	36.60±5.94	38.24±5.09

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	0.34±0.25	0.30±0.14	0.44±0.29	0.43±0.35	0.28±0.07	0.21±0.04
Sati.	0.00±0.00	82.58±17.29	32.41±31.03	0.98±0.08	0.97±0.12	0.95±0.08	0.95±0.11
Shut.	0.00±0.00	14.56±9.33	14.81±7.82	15.00±5.65	21.26±10.20	23.99±7.58	23.66±8.19
WBC	0.00±0.00	69.83±1.70	66.85±4.56	55.48±5.33	52.59±7.75	53.91±7.58	56.14±5.27
Thyr.	0.00±0.00	19.45±9.22	21.10±3.93	39.63±14.47	30.15±13.86	22.16±5.90	27.85±7.67
WDBC	0.00±0.00	69.92±4.90	49.48±11.87	65.32±7.40	69.38±3.47	67.34±5.31	68.56±2.15
Optd.	0.00±0.00	5.96±3.01	7.71±9.46	2.56±0.33	2.47±0.31	2.46±0.24	2.47±0.20
Wave.	0.00±0.00	3.54±1.17	3.70±0.85	3.78±0.60	3.35±0.45	3.36±0.45	3.36±0.47
Musk	0.00±0.00	9.71±23.69	78.08±35.37	97.22±8.27	84.20±22.66	81.58±23.15	97.43±6.58
Vowe.	0.00±0.00	32.08±18.26	10.08±6.52	18.63±9.69	23.20±6.44	23.56±9.40	22.77±4.36
Lymp.	0.00±0.00	64.41±0.14	73.34±6.65	61.34±7.02	52.33±5.77	50.98±7.39	53.23±7.94
Glass	0.00±0.00	2.96±1.22	10.91±3.53	12.24±4.92	15.05±4.88	16.29±4.87	13.05±5.18
Wilt	0.00±0.00	3.38±0.22	4.13±0.66	4.72±0.32	4.77±0.53	4.26±0.32	4.44±0.23
Lett.	0.00±0.00	7.83±1.27	5.52±0.96	7.05±1.53	8.72±1.68	8.77±0.82	9.21±1.25
Annt.	0.00±0.00	9.87±1.68	9.27±0.90	9.87±0.29	9.45±0.24	9.18±0.38	9.95±1.25
Wine	0.00±0.00	36.30±14.39	18.69±9.27	18.92±8.81	13.18±4.82	19.68±7.82	14.95±4.92
Stam.	0.00±0.00	20.30±6.44	28.26±14.20	26.87±8.40	24.27±4.45	22.25±3.05	20.71±1.87
Mnist	0.00±0.00	24.34±6.74	25.33±7.16	24.54±3.85	15.30±7.52	12.57±0.95	14.92±4.40
Page.	0.00±0.00	39.02±8.34	44.57±4.95	48.33±6.19	46.74±6.68	46.19±5.71	46.20±10.02
Vert.	0.00±0.00	8.71±0.45	9.47±0.70	8.83±0.47	8.59±0.30	8.60±0.22	8.62±0.27
Card.	0.00±0.00	31.48±7.97	30.96±4.57	30.99±3.85	27.60±1.26	27.25±2.24	25.64±1.40
WPBC	0.00±0.00	25.94±1.57	22.64±2.39	21.24±1.17	20.33±0.44	20.43±0.96	19.89±0.51
Sate.	0.00±0.00	50.69±4.67	37.00±7.43	39.53±3.38	47.06±4.23	46.74±4.56	49.84±7.12
Pima	0.00±0.00	60.25±1.65	45.91±3.09	42.57±2.08	40.03±0.93	39.82±0.90	39.35±0.65
Brea.	0.00±0.00	99.01±0.10	39.66±2.11	41.25±0.80	40.12±0.80	40.86±0.73	40.53±1.06
Iono.	0.00±0.00	57.79±8.11	71.05±6.85	85.55±4.83	85.62±3.71	83.84±6.23	85.35±1.93
Spam.	0.00±0.00	45.91±4.00	33.26±2.58	35.56±1.94	37.46±2.50	38.57±1.69	39.19±2.89
Hear.	0.00±0.00	73.64±5.70	51.13±8.42	46.26±4.29	49.75±2.88	48.05±2.69	49.30±2.34
Arrh.	0.00±0.00	55.06±6.75	52.13±1.58	55.06±4.69	62.24±1.72	62.54±1.78	62.38±2.42
Park.	0.00±0.00	90.89±2.96	76.90±4.88	75.11±2.53	74.31±2.74	73.90±2.97	74.45±2.37

Table A25: S-DRL's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	55.85±17.91	67.38±20.09	73.98±8.62	51.65±5.65	56.11±11.92	52.32±3.61
Sati.	0.00±0.00	86.53±12.59	96.34±1.59	85.89±9.78	94.82±2.20	93.80±3.01	89.69±7.46
Shut.	0.00±0.00	87.97±8.05	87.13±11.22	95.38±4.12	98.59±1.10	98.52±2.11	99.02±0.64
WBC	0.00±0.00	98.35±0.28	98.08±0.63	97.79±0.51	97.77±0.35	97.72±0.34	98.02±0.32
Thyr.	0.00±0.00	85.88±6.17	95.33±1.96	96.43±1.61	93.96±1.77	95.72±2.04	94.31±2.58
WDBC	0.00±0.00	97.08±1.17	95.36±1.53	95.25±1.36	95.68±1.69	95.81±1.23	96.11±1.15
Optd.	0.00±0.00	63.89±10.80	49.78±6.95	47.59±7.80	44.43±4.05	45.64±2.91	44.05±3.75
Wave.	0.00±0.00	50.42±11.26	56.67±3.85	58.09±4.72	54.72±3.12	53.50±1.59	53.48±1.72
Musk	0.00±0.00	0.03±0.04	68.59±21.01	86.06±13.28	99.02±1.22	99.94±0.09	99.37±1.26
Vowe.	0.00±0.00	72.61±8.05	72.79±10.74	81.95±6.68	93.32±2.24	94.71±1.78	92.81±2.15
Lymp.	0.00±0.00	73.96±1.43	91.85±2.53	93.73±1.53	92.50±2.23	92.93±1.47	91.07±2.59
Glass	0.00±0.00	22.02±10.30	72.80±5.24	77.11±5.55	77.57±7.13	78.41±4.33	78.54±5.85
Wilt	0.00±0.00	31.08±6.80	46.44±8.80	53.18±6.91	50.88±4.17	49.36±3.98	47.25±3.98
Lett.	0.00±0.00	54.96±2.16	44.43±4.74	52.33±5.85	60.51±3.80	64.94±4.73	65.67±4.51
Annt.	0.00±0.00	56.42±7.15	60.06±3.58	65.90±5.59	66.17±3.92	62.25±1.56	64.84±3.52
Wine	0.00±0.00	90.32±4.70	81.24±7.52	91.72±5.98	96.13±3.74	97.70±1.39	96.60±2.67
Stam.	0.00±0.00	62.61±13.54	86.19±7.90	84.88±6.63	86.04±6.59	87.59±5.87	87.12±7.89
Mnist	0.00±0.00	66.19±9.81	76.05±3.97	74.70±2.05	66.70±6.66	66.86±7.75	72.85±9.04
Page.	0.00±0.00	82.13±6.20	90.13±2.35	93.65±1.01	93.78±1.29	93.24±1.86	93.52±1.26
Vert.	0.00±0.00	33.02±3.15	41.37±4.72	40.93±4.38	37.09±2.64	38.14±3.97	38.19±2.93
Card.	0.00±0.00	55.54±7.88	64.28±8.00	65.33±4.18	61.64±3.49	61.71±2.58	60.86±3.16
WPBC	0.00±0.00	55.92±1.70	49.88±4.50	48.63±4.16	48.56±3.08	46.74±2.94	49.00±3.38
Sate.	0.00±0.00	47.16±2.21	67.41±2.66	72.48±0.83	73.57±1.18	73.31±1.21	74.79±2.33
Pima	0.00±0.00	75.83±2.57	69.22±3.90	69.12±1.54	68.49±1.57	67.28±1.42	68.71±1.33
Brea.	0.00±0.00	99.46±0.05	99.17±0.12	98.96±0.15	98.89±0.15	98.88±0.12	98.78±0.12
Iono.	0.00±0.00	56.30±6.81	84.34±5.32	92.16±1.46	95.04±1.26	93.77±1.51	95.20±1.20
Spam.	0.00±0.00	51.65±9.43	75.21±3.23	72.90±3.93	72.48±2.05	71.64±2.98	70.55±2.13
Hear.	0.00±0.00	82.78±2.39	73.50±3.78	78.82±2.47	83.49±1.58	81.00±2.23	82.22±2.08
Arrh.	0.00±0.00	54.99±4.17	53.57±5.11	54.88±5.95	66.96±2.44	65.95±2.36	66.59±3.43
Park.	0.00±0.00	80.52±2.53	79.87±4.41	84.87±5.31	88.32±2.80	87.49±1.72	87.82±2.80

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	0.52±0.94	0.72±0.82	0.79±0.59	0.24±0.04	0.37±0.27	0.30±0.07
Sati.	0.00±0.00	58.73±33.99	86.00±6.41	41.71±39.73	72.11±20.29	65.41±19.94	48.07±36.24
Shut.	0.00±0.00	19.05±10.44	14.70±10.42	31.54±14.19	42.45±10.06	45.00±13.87	47.40±11.51
WBC	0.00±0.00	66.56±3.83	67.28±2.96	61.76±2.85	60.99±2.00	60.84±2.31	63.75±1.91
Thyr.	0.00±0.00	22.12±4.47	51.21±11.99	60.55±8.88	43.54±9.25	51.93±13.17	46.54±10.97
WDBC	0.00±0.00	64.67±13.76	68.77±8.61	76.52±2.77	76.48±2.58	76.65±3.10	77.11±2.67
Optd.	0.00±0.00	4.25±1.37	2.89±0.62	2.71±0.49	2.49±0.17	2.55±0.11	2.50±0.14
Wave.	0.00±0.00	3.13±1.00	3.92±0.58	4.34±1.34	3.59±0.81	3.41±0.46	3.22±0.37
Musk	0.00±0.00	1.60±0.00	10.36±10.34	35.23±29.62	81.66±19.57	98.45±2.20	90.76±13.91
Vowe.	0.00±0.00	13.39±13.82	11.81±7.13	24.87±19.66	43.65±10.48	49.82±11.33	39.77±9.92
Lymp.	0.00±0.00	63.94±0.96	73.54±2.42	75.27±0.51	75.15±0.92	75.73±0.87	75.53±1.02
Glass	0.00±0.00	2.59±0.34	13.01±5.48	20.32±3.46	21.91±2.45	22.14±3.24	22.89±3.65
Wilt	0.00±0.00	3.55±0.32	4.69±1.02	5.43±0.83	5.09±0.39	4.94±0.36	4.73±0.41
Lett.	0.00±0.00	7.33±0.73	5.97±1.67	8.35±2.51	12.48±2.78	16.26±4.93	15.92±3.81
Annt.	0.00±0.00	9.02±1.26	12.51±2.54	23.69±3.73	26.52±2.82	23.21±1.73	24.87±2.14
Wine	0.00±0.00	35.02±11.69	23.71±18.97	53.45±22.68	72.27±21.59	76.32±15.19	66.25±20.76
Stam.	0.00±0.00	15.99±4.81	33.23±11.54	35.59±11.37	34.58±10.63	36.39±10.83	37.75±10.12
Mnist	0.00±0.00	23.00±5.79	27.58±3.49	31.48±3.09	26.09±5.79	26.85±6.82	32.95±8.16
Page.	0.00±0.00	37.04±5.51	56.91±7.90	69.77±2.33	70.33±2.71	68.13±4.74	69.24±3.18
Vert.	0.00±0.00	8.74±0.35	9.86±0.84	9.73±0.68	9.15±0.32	9.31±0.55	9.29±0.43
Card.	0.00±0.00	26.02±4.93	38.66±10.21	38.40±4.93	38.30±4.26	37.48±3.31	36.83±3.67
WPBC	0.00±0.00	25.52±1.36	24.05±2.24	22.87±2.17	22.91±2.31	21.97±1.61	22.85±1.83
Sate.	0.00±0.00	41.97±7.05	67.22±2.82	72.57±1.35	74.06±1.86	73.95±1.48	75.56±2.06
Pima	0.00±0.00	59.28±2.43	51.94±3.64	53.18±1.52	55.13±2.44	54.24±1.66	55.04±1.76
Brea.	0.00±0.00	98.96±0.11	98.44±0.32	97.99±0.36	97.72±0.31	97.63±0.24	97.37±0.31
Iono.	0.00±0.00	53.65±6.94	81.38±4.67	89.52±1.72	93.32±1.74	91.43±2.14	93.22±2.00
Spam.	0.00±0.00	43.42±7.07	74.70±3.70	71.23±4.27	71.09±2.12	70.29±2.81	69.30±2.50
Hear.	0.00±0.00	77.19±3.46	67.70±4.82	75.46±4.49	82.77±1.79	79.25±3.51	81.05±2.68
Arrh.	0.00±0.00	56.29±3.93	54.52±3.85	55.07±5.47	64.72±2.75	63.59±2.89	63.49±2.49
Park.	0.00±0.00	93.75±0.96	92.77±1.51	94.88±2.18	96.10±0.97	95.87±0.60	96.03±0.93

Table A26: FEAWAD's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	52.84±22.30	59.66±20.45	97.70±2.11	94.82±4.47	95.30±5.95	94.69±7.90
Sati.	0.00±0.00	50.39±24.95	45.98±24.37	99.41±0.25	98.95±1.45	99.12±0.76	99.16±0.92
Shut.	0.00±0.00	47.99±35.41	62.21±31.05	90.00±29.95	90.44±28.61	90.89±27.27	93.21±20.28
WBC	0.00±0.00	51.27±41.98	52.75±40.51	95.66±2.76	94.63±6.18	94.93±6.17	94.96±5.00
Thyr.	0.00±0.00	49.84±35.85	50.54±34.08	98.94±1.85	98.40±1.73	98.44±2.07	98.53±1.82
WDBC	0.00±0.00	61.97±41.63	43.13±44.66	96.52±2.58	96.48±1.62	94.76±4.38	96.10±2.29
Optd.	0.00±0.00	46.48±25.41	56.23±27.30	97.44±1.66	95.42±5.60	95.20±4.46	94.47±4.71
Wave.	0.00±0.00	49.99±10.95	49.04±10.58	75.74±5.83	76.50±7.09	76.87±5.37	73.79±10.34
Musk	0.00±0.00	43.75±31.83	63.12±27.17	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Vowe.	0.00±0.00	67.00±20.69	69.57±17.51	91.71±3.25	91.54±4.44	91.27±5.09	90.24±6.41
Lymp.	0.00±0.00	41.96±31.39	45.88±34.27	85.60±5.23	84.99±4.08	86.76±3.65	86.46±4.52
Glass	0.00±0.00	40.19±22.75	46.82±26.47	63.49±7.39	70.37±12.94	62.43±13.74	64.20±11.83
Wilt	0.00±0.00	48.00±14.59	49.25±15.12	68.92±11.81	66.19±18.75	66.40±19.30	65.82±19.93
Lett.	0.00±0.00	50.34±4.60	52.35±6.62	64.39±3.87	67.27±2.08	66.52±3.03	66.80±3.56
Annt.	0.00±0.00	52.47±13.47	47.06±16.84	85.28±2.36	85.65±4.21	86.43±2.29	86.28±2.86
Wine	0.00±0.00	22.78±33.67	23.29±33.85	82.29±12.35	72.38±17.32	71.65±16.09	77.74±12.50
Stam.	0.00±0.00	59.98±27.23	62.65±21.94	91.41±3.90	86.43±8.11	84.10±9.42	82.98±10.44
Mnist	0.00±0.00	43.77±11.27	36.04±16.69	94.29±2.01	93.53±3.05	93.80±2.26	94.57±2.87
Page.	0.00±0.00	45.75±9.75	47.05±13.10	85.24±17.31	88.77±9.62	90.09±4.24	91.19±1.88
Vert.	0.00±0.00	44.47±13.11	44.48±17.87	78.39±10.72	72.66±7.74	73.71±10.06	74.30±10.15
Card.	0.00±0.00	46.50±17.02	42.31±16.64	93.04±2.71	93.26±0.85	93.18±0.95	91.86±3.94
WPBC	0.00±0.00	50.72±5.68	50.19±5.17	55.63±5.44	54.51±5.68	57.00±2.47	56.61±2.64
Sate.	0.00±0.00	48.27±10.21	48.26±12.12	84.51±3.41	85.85±4.02	85.08±4.17	85.61±3.75
Pima	0.00±0.00	42.22±19.84	40.33±18.16	78.12±2.69	77.10±3.20	76.14±3.37	78.06±3.08
Brea.	0.00±0.00	49.66±46.24	55.13±44.56	98.53±1.35	97.31±2.65	97.07±2.81	97.29±2.63
Iono.	0.00±0.00	46.39±14.95	42.70±14.97	79.75±5.94	62.35±13.12	64.10±16.29	65.77±15.32
Spam.	0.00±0.00	53.76±11.62	49.33±10.82	91.33±1.69	89.35±2.63	90.13±2.58	88.22±5.13
Hear.	0.00±0.00	31.51±23.08	31.06±24.40	71.55±7.24	72.66±7.15	72.96±8.43	69.78±8.54
Arrh.	0.00±0.00	0.00±0.00	53.30±3.82	48.99±12.23	61.89±9.47	69.11±4.54	67.83±2.97
Park.	0.00±0.00	49.15±22.80	45.84±17.02	59.80±4.37	60.88±6.12	58.55±7.48	58.62±8.04

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	0.38±0.41	0.35±0.23	55.08±14.00	56.99±9.56	59.84±11.77	58.52±8.75
Sati.	0.00±0.00	8.00±19.56	4.86±10.74	89.06±3.78	90.25±2.83	89.91±2.07	89.02±4.14
Shut.	0.00±0.00	14.06±29.26	11.28±14.80	88.33±29.56	87.42±29.56	87.58±29.60	85.33±29.27
WBC	0.00±0.00	31.57±32.51	32.88±31.69	56.63±6.47	54.36±10.36	54.77±9.49	54.10±10.54
Thyr.	0.00±0.00	22.75±26.50	25.62±30.01	87.51±2.18	83.51±9.71	83.74±10.50	84.60±8.48
WDBC	0.00±0.00	39.70±32.00	28.69±33.39	71.73±18.60	62.15±16.36	62.09±18.00	65.28±17.22
Optd.	0.00±0.00	3.27±1.82	8.69±11.02	93.63±2.68	89.18±9.30	88.21±7.36	84.98±9.43
Wave.	0.00±0.00	3.15±1.05	3.03±0.89	16.94±3.85	16.40±4.30	16.28±5.31	15.42±3.85
Musk	0.00±0.00	14.02±23.91	18.96±21.33	100.00±0.00	100.00±0.00	100.00±0.00	99.99±0.04
Vowe.	0.00±0.00	14.38±15.48	18.29±19.53	70.00±4.26	70.65±7.44	70.24±8.90	71.65±5.51
Lymp.	0.00±0.00	27.44±28.97	24.75±25.55	61.42±6.40	59.19±7.63	59.58±7.57	60.28±7.31
Glass	0.00±0.00	5.52±6.09	5.97±3.77	22.12±6.93	24.13±6.77	23.91±6.48	23.43±4.93
Wilt	0.00±0.00	5.37±2.16	5.64±2.63	10.18±4.44	10.34±3.86	10.36±3.90	10.44±3.96
Lett.	0.00±0.00	7.36±1.27	7.76±1.17	17.40±2.94	19.62±2.73	18.18±3.12	18.59±4.84
Annt.	0.00±0.00	11.77±8.86	10.45±8.79	38.93±14.22	37.11±15.96	39.09±13.19	39.72±14.99
Wine	0.00±0.00	10.36±13.85	10.71±13.85	74.00±13.43	50.76±18.51	49.28±13.21	55.72±17.53
Stam.	0.00±0.00	24.63±20.17	22.92±19.99	58.86±12.94	55.20±9.56	52.05±12.12	50.34±12.35
Mnist	0.00±0.00	10.99±3.86	10.62±6.56	75.51±7.46	76.85±2.82	74.24±6.14	75.95±5.01
Page.	0.00±0.00	23.69±10.68	22.33±10.65	58.32±16.73	61.42±12.26	61.34±10.20	63.36±9.27
Vert.	0.00±0.00	10.97±2.70	11.65±3.93	51.96±8.08	45.44±9.61	47.36±12.07	46.73±10.28
Card.	0.00±0.00	25.03±10.24	23.45±9.27	80.78±7.40	78.93±3.55	78.75±4.37	77.34±6.58
WPBC	0.00±0.00	23.58±3.59	22.71±2.41	34.40±4.75	34.63±4.54	35.74±3.42	36.61±2.80
Sate.	0.00±0.00	35.17±9.56	34.52±10.33	79.63±3.42	80.78±3.36	79.85±2.50	79.47±3.09
Pima	0.00±0.00	35.01±13.38	33.18±12.59	62.61±5.27	61.18±4.36	59.15±4.64	62.13±4.46
Brea.	0.00±0.00	57.71±37.83	60.35±37.26	96.83±2.72	95.03±4.40	95.01±4.83	94.93±4.76
Iono.	0.00±0.00	44.44±12.88	39.27±12.58	79.19±5.04	61.30±11.40	63.89±13.33	65.44±13.31
Spam.	0.00±0.00	44.58±8.45	40.63±9.82	86.84±1.88	86.45±2.41	87.49±2.47	83.95±9.33
Hear.	0.00±0.00	38.36±15.98	38.74±16.88	71.92±4.83	71.65±4.11	72.66±5.47	70.25±6.01
Arrh.	0.00±0.00	0.00±0.00	54.18±3.61	51.15±11.14	62.56±9.07	69.84±4.04	69.19±2.26
Park.	0.00±0.00	77.80±11.55	75.13±8.66	81.59±2.21	82.57±3.51	80.96±4.59	81.01±4.22

Table A27: MLP's results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	43.02±21.67	48.64±24.10	38.06±8.43	44.72±14.90	54.06±15.50	54.43±15.54
Sati.	0.00±0.00	55.57±29.02	51.62±29.75	98.86±0.59	98.43±1.06	98.33±1.04	98.43±0.85
Shut.	0.00±0.00	39.50±44.03	36.58±39.51	27.35±36.58	21.87±20.82	29.37±31.54	29.47±31.67
WBC	0.00±0.00	49.10±42.32	51.18±40.67	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Thyr.	0.00±0.00	48.19±29.73	54.64±29.31	99.57±0.42	99.63±0.35	99.62±0.35	99.62±0.35
WDBC	0.00±0.00	44.58±28.01	50.76±25.27	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Optd.	0.00±0.00	36.06±12.16	45.74±21.28	99.99±0.00	99.98±0.00	99.98±0.01	99.98±0.00
Wave.	0.00±0.00	40.84±10.66	41.53±12.65	93.21±0.78	93.61±0.75	93.48±0.86	93.51±0.80
Musk	0.00±0.00	53.36±21.63	29.03±18.59	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Vowe.	0.00±0.00	60.07±14.99	53.40±14.49	97.57±5.49	99.40±0.84	99.40±0.79	99.39±0.81
Lymp.	0.00±0.00	46.90±43.87	58.62±42.93	88.97±20.45	98.62±3.16	98.62±3.16	98.62±3.16
Glass	0.00±0.00	52.32±34.92	52.56±41.00	92.20±0.81	92.68±0.94	92.68±0.94	92.68±0.94
Wilt	0.00±0.00	48.92±12.73	48.58±14.13	66.28±5.05	66.13±5.80	66.27±5.83	61.28±20.53
Lett.	0.00±0.00	42.77±6.22	44.42±6.74	89.21±3.41	89.57±2.10	89.11±1.99	89.05±2.03
Annt.	0.00±0.00	43.91±16.86	46.62±18.64	91.97±1.50	92.20±1.12	92.23±1.12	92.21±1.11
Wine	0.00±0.00	42.29±35.32	41.46±32.39	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Stam.	0.00±0.00	38.49±35.89	43.52±32.52	93.51±5.14	97.53±0.87	97.42±0.92	97.47±0.94
Mnist	0.00±0.00	45.74±14.51	56.03±16.24	99.22±0.15	99.30±0.18	99.27±0.17	99.33±0.15
Page.	0.00±0.00	43.74±12.98	45.69±12.30	93.99±1.08	93.68±1.05	93.68±1.02	93.67±1.05
Vert.	0.00±0.00	45.75±21.02	53.21±14.43	80.32±4.68	80.91±4.76	80.79±4.84	80.83±4.85
Card.	0.00±0.00	44.10±17.31	45.70±15.29	98.53±0.17	98.55±0.15	98.57±0.16	98.57±0.17
WPBC	0.00±0.00	51.83±13.88	55.09±12.78	84.66±2.46	85.66±3.39	85.88±2.58	85.20±3.76
Sate.	0.00±0.00	54.11±16.93	54.59±16.87	93.85±2.12	92.07±2.58	92.01±2.77	92.03±2.80
Pima	0.00±0.00	51.19±20.18	50.23±20.43	89.03±0.39	89.00±0.56	88.91±0.44	88.99±0.50
Brea.	0.00±0.00	47.20±35.72	48.40±36.33	99.02±0.04	98.99±0.05	98.99±0.04	99.00±0.04
Iono.	0.00±0.00	47.49±12.91	42.72±12.53	95.57±1.01	95.58±0.93	95.52±0.89	95.49±0.93
Spam.	0.00±0.00	47.33±5.50	49.21±15.78	97.77±0.07	97.65±0.13	97.66±0.13	97.66±0.12
Hear.	0.00±0.00	55.58±18.37	53.46±16.01	85.83±0.93	85.46±0.99	85.67±1.16	85.72±1.02
Arrh.	0.00±0.00	0.00±0.00	52.73±9.49	76.94±0.84	77.55±0.57	78.51±0.46	78.58±0.55
Park.	0.00±0.00	46.83±21.18	56.28±15.77	95.52±1.81	95.07±1.94	94.76±1.77	94.83±1.82

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.00±0.00	0.30±0.40	0.28±0.22	0.16±0.02	0.20±0.08	0.27±0.13	0.27±0.13
Sati.	0.00±0.00	6.91±6.87	14.85±24.81	88.73±2.36	89.52±1.59	89.27±0.98	89.21±1.02
Shut.	0.00±0.00	17.87±31.79	9.69±22.33	20.62±39.69	4.50±11.01	14.41±30.56	14.41±30.56
WBC	0.00±0.00	22.55±32.88	30.43±32.98	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Thyr.	0.00±0.00	19.43±30.05	20.73±25.87	90.98±1.18	91.14±1.00	91.19±1.03	91.19±1.03
WDBC	0.00±0.00	13.34±20.62	10.58±14.11	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Optd.	0.00±0.00	2.12±0.39	2.89±1.07	99.57±0.09	99.35±0.11	99.43±0.12	99.44±0.11
Wave.	0.00±0.00	2.98±1.90	2.96±1.36	37.86±8.93	43.77±1.89	43.59±2.10	43.48±2.34
Musk	0.00±0.00	7.05±8.86	2.64±0.88	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Vowe.	0.00±0.00	7.05±5.02	5.88±5.07	81.32±19.35	89.89±9.14	89.47±8.71	89.43±8.81
Lymp.	0.00±0.00	24.54±38.35	42.08±47.33	65.63±42.66	83.75±32.62	83.75±32.62	83.75±32.62
Glass	0.00±0.00	11.10±10.16	17.45±19.50	21.01±1.62	22.00±1.95	22.00±1.95	22.00±1.95
Wilt	0.00±0.00	5.15±1.60	9.62±13.99	9.00±0.74	8.47±2.10	8.51±2.11	8.24±2.86
Lett.	0.00±0.00	6.06±2.31	6.22±2.13	62.16±11.08	63.21±5.70	62.98±6.45	62.46±5.90
Annt.	0.00±0.00	8.33±6.00	9.34±6.04	63.42±2.90	63.51±2.68	63.57±2.73	63.49±2.71
Wine	0.00±0.00	22.01±32.48	16.81±28.13	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Stam.	0.00±0.00	14.38±15.37	16.45±21.58	66.51±20.42	79.76±8.47	78.61±8.76	80.11±9.25
Mnist	0.00±0.00	15.54±7.75	20.62±9.94	93.08±0.44	93.44±0.54	93.59±0.55	93.67±0.64
Page.	0.00±0.00	24.33±10.92	24.55±8.19	75.16±2.57	75.76±2.20	75.80±2.18	75.79±2.18
Vert.	0.00±0.00	12.88±7.89	13.13±3.72	27.33±6.79	27.94±6.97	27.87±7.03	27.90±7.03
Card.	0.00±0.00	24.93±14.32	24.12±11.81	95.70±0.36	95.69±0.35	95.69±0.33	95.70±0.35
WPBC	0.00±0.00	27.56±7.72	27.35±10.71	65.90±5.04	67.29±7.27	67.38±6.52	66.24±7.77
Sate.	0.00±0.00	41.14±15.76	42.77±16.79	90.66±2.34	88.83±2.85	88.76±3.00	88.78±3.02
Pima	0.00±0.00	41.94±17.15	41.28±16.95	80.77±0.67	80.57±1.29	80.46±1.20	80.46±1.37
Brea.	0.00±0.00	52.51±28.30	53.92±29.16	98.16±0.08	98.10±0.09	98.10±0.06	98.11±0.08
Iono.	0.00±0.00	43.98±11.14	35.67±7.56	94.42±1.18	94.38±1.03	94.28±0.98	94.28±0.99
Spam.	0.00±0.00	39.25±4.82	42.64±12.70	96.85±0.28	96.83±0.31	96.85±0.35	96.85±0.34
Hear.	0.00±0.00	52.48±14.54	51.28±13.20	85.19±1.60	84.91±2.00	84.71±2.11	84.81±1.99
Arrh.	0.00±0.00	0.00±0.00	53.76±8.54	76.79±0.63	77.17±0.64	79.43±0.48	79.47±0.54
Park.	0.00±0.00	73.26±11.06	78.49±8.76	98.31±0.70	98.15±0.74	98.04±0.66	98.06±0.69

Table A28: AE(Layers=2, ReLU=yes, Bias=yes, loss=L1, scoring=L1)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	68.40±0.00	68.84±1.94	69.05±2.29	58.38±15.66	58.76±15.49	58.73±15.49	58.74±15.48
Sati.	43.38±0.00	50.86±2.68	50.26±2.08	98.13±0.96	97.91±1.83	97.92±1.80	97.93±1.78
Shut.	85.37±0.00	76.01±30.14	75.88±30.52	79.79±22.25	79.50±22.13	79.51±22.13	79.51±22.13
WBC	98.83±0.00	89.53±12.36	89.80±11.32	97.63±3.31	97.67±3.27	97.67±3.27	97.67±3.27
Thyr.	32.29±11.91	62.12±27.38	63.08±26.43	66.84±22.71	68.17±22.69	68.20±22.69	68.20±22.69
WDBC	98.15±0.00	97.35±0.70	97.53±0.53	95.89±1.09	95.70±1.53	95.75±1.48	95.76±1.48
Optd.	61.43±0.00	58.50±20.09	54.57±20.14	62.88±15.11	63.04±15.38	63.54±15.36	63.53±15.37
Wave.	45.64±0.00	49.03±5.32	48.29±4.90	60.41±12.87	60.62±12.99	60.61±13.01	60.61±13.01
Musk	0.17±0.00	2.98±2.36	1.43±0.76	98.15±2.32	98.18±3.20	98.29±3.21	98.33±3.15
Vowe.	87.84±0.00	84.74±5.92	85.69±4.42	63.62±14.51	61.97±15.53	61.99±15.52	61.99±15.52
Lymp.	55.06±31.15	68.83±22.31	67.35±23.17	69.37±23.57	69.31±23.60	69.31±23.60	69.31±23.60
Glass	23.92±10.13	28.34±11.36	27.19±13.02	51.04±19.54	50.47±19.12	50.47±19.09	50.47±19.09
Wilt	35.52±4.02	40.44±12.27	39.77±11.59	38.00±6.82	37.88±7.20	37.89±7.21	37.89±7.21
Lett.	57.03±0.00	56.78±0.52	56.72±0.63	52.46±3.39	52.56±3.34	52.52±3.34	52.38±3.52
Annt.	38.60±0.00	50.94±10.74	52.04±11.10	51.59±6.91	51.06±6.91	50.99±6.82	51.01±6.83
Wine	96.55±0.00	95.70±0.74	95.87±0.78	86.51±11.23	85.61±11.54	85.61±11.54	85.61±11.54
Stam.	63.43±0.00	66.93±15.00	66.59±15.69	72.10±9.98	72.34±10.48	72.32±10.53	72.32±10.53
Mnist	39.78±0.00	62.20±11.06	61.97±8.77	69.34±5.70	71.06±5.06	71.13±5.05	71.14±5.07
Page.	67.65±0.00	45.95±14.05	47.97±16.55	57.50±13.62	58.86±12.78	58.82±12.79	58.82±12.79
Vert.	32.47±1.24	35.97±15.04	35.41±12.26	31.90±8.21	31.65±8.49	31.70±8.53	31.71±8.53
Card.	53.69±0.00	56.72±10.24	57.71±9.11	69.23±7.00	69.10±6.13	69.02±6.14	69.01±6.14
WPBC	56.87±0.00	56.59±0.41	56.78±0.45	54.66±1.56	54.45±1.76	54.49±1.73	54.46±1.78
Sate.	32.22±0.00	33.42±0.61	33.28±0.53	55.40±2.51	55.23±2.52	55.31±2.55	55.31±2.55
Pima	75.42±0.00	74.54±2.02	74.38±2.01	73.53±3.46	73.53±3.58	73.53±3.58	73.53±3.58
Brea.	99.52±0.00	94.01±9.63	95.35±6.00	98.83±1.27	98.88±1.09	98.87±1.12	98.87±1.11
Iono.	25.51±0.00	26.34±0.62	26.26±0.65	68.77±4.39	68.88±4.16	68.85±4.22	68.84±4.21
Spam.	68.33±0.00	54.47±11.51	52.72±12.62	66.06±0.92	66.10±0.75	66.22±0.82	66.23±0.84
Hear.	86.03±0.00	84.02±2.20	84.54±1.94	79.14±4.24	78.96±4.58	78.99±4.55	78.99±4.55
Arrh.	52.08±0.00	51.47±0.41	51.84±0.45	71.63±1.62	72.03±1.05	72.51±1.44	72.19±1.30
Park.	83.86±0.00	80.37±3.17	80.95±2.56	65.31±4.51	65.71±5.07	65.72±5.05	65.71±5.07

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.35±0.00	0.35±0.04	0.36±0.07	0.27±0.15	0.29±0.19	0.29±0.20	0.29±0.20
Sati.	1.00±0.00	1.14±0.06	1.13±0.04	89.94±5.06	88.76±10.23	88.83±10.16	88.88±10.03
Shut.	16.10±0.00	19.89±18.94	18.64±17.69	10.67±4.60	10.47±4.46	10.54±4.49	10.54±4.49
WBC	71.51±0.00	56.71±15.82	56.49±16.22	69.98±5.40	70.23±4.86	70.30±4.90	70.22±4.86
Thyr.	4.59±5.54	23.02±22.78	22.55±23.16	19.81±21.75	20.15±21.67	20.20±21.74	20.20±21.74
WDBC	76.51±0.00	73.13±2.82	73.78±2.75	65.48±5.08	64.24±6.61	64.23±6.60	64.35±6.65
Optd.	3.92±0.00	4.41±2.76	3.78±2.09	4.48±2.05	4.51±2.05	4.58±2.02	4.58±2.02
Wave.	2.57±0.00	2.88±0.56	2.82±0.52	4.21±1.49	4.25±1.54	4.25±1.55	4.25±1.55
Musk	1.60±0.00	1.62±0.02	1.61±0.01	77.70±22.87	81.93±24.94	83.07±24.32	83.19±24.22
Vowe.	39.26±0.00	28.26±16.14	29.27±14.79	10.95±11.51	10.12±11.03	10.15±11.08	10.15±11.08
Lymp.	44.32±28.69	44.68±28.43	44.09±29.00	48.43±29.23	48.42±29.24	48.42±29.24	48.42±29.24
Glass	2.75±0.72	2.97±0.81	2.98±0.87	5.13±2.39	5.02±2.32	5.02±2.31	5.02±2.31
Wilt	3.75±0.24	4.31±1.24	4.23±1.13	3.92±0.35	3.92±0.39	3.92±0.39	3.92±0.39
Lett.	7.41±0.00	7.39±0.14	7.38±0.14	6.94±0.84	6.98±0.87	6.97±0.88	6.94±0.90
Annt.	5.68±0.00	9.11±3.34	9.64±3.70	8.46±1.69	8.37±1.64	8.34±1.62	8.35±1.62
Wine	52.47±0.00	50.12±2.27	51.10±2.75	35.51±16.11	33.98±16.72	33.98±16.73	33.98±16.73
Stam.	14.35±0.00	18.09±7.56	18.07±7.40	18.97±5.47	19.07±5.22	19.06±5.24	19.07±5.24
Mnist	10.56±0.00	22.71±7.48	22.14±6.31	24.86±3.22	26.01±3.12	26.03±3.05	26.07±3.11
Page.	31.00±0.00	26.00±11.46	27.62±13.53	30.16±11.14	30.73±10.77	30.73±10.78	30.74±10.78
Vert.	8.63±0.14	10.10±4.00	9.33±1.84	8.70±1.05	8.69±1.11	8.70±1.12	8.70±1.12
Card.	23.39±0.00	29.54±5.75	29.31±5.45	39.45±4.83	39.08±4.34	38.97±4.46	38.97±4.46
WPBC	26.17±0.00	25.89±0.27	26.01±0.40	24.65±1.16	24.51±1.23	24.52±1.22	24.51±1.24
Sate.	22.86±0.00	23.17±0.16	23.14±0.13	53.24±3.28	52.98±3.21	53.04±3.23	53.04±3.22
Pima	62.14±0.00	61.02±1.63	60.91±1.55	59.11±3.87	59.09±3.98	59.09±3.98	59.09±3.98
Brea.	99.06±0.00	93.64±9.05	94.83±5.82	98.30±1.27	98.35±1.11	98.34±1.13	98.34±1.13
Iono.	25.83±0.00	26.28±0.36	26.24±0.33	60.72±5.55	61.09±5.16	61.06±5.17	61.04±5.16
Spam.	52.54±0.00	43.44±7.54	42.16±8.08	49.85±0.84	49.91±0.85	50.01±0.88	50.00±0.88
Hear.	84.10±0.00	81.18±3.42	81.68±2.85	74.89±5.57	74.60±6.05	74.62±6.02	74.63±6.03
Arrh.	53.32±0.00	53.00±0.48	53.09±0.37	71.73±1.64	72.03±1.10	72.50±1.52	72.24±1.14
Park.	94.84±0.00	93.58±1.21	93.83±0.96	87.43±2.09	87.65±2.40	87.65±2.39	87.65±2.41

Table A29: AE(Layers=3, ReLU=yes, Bias=yes, loss=L1, scoring=L1)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	68.40±0.00	68.30±0.64	68.46±0.71	61.22±21.87	58.48±22.75	58.46±22.75	58.46±22.75
Sati.	43.38±0.00	49.12±2.64	48.20±2.16	95.37±2.20	96.22±1.78	96.19±1.82	96.19±1.82
Shut.	85.37±0.00	72.72±33.99	73.57±33.15	82.09±18.22	81.98±17.33	81.93±17.37	81.95±17.39
WBC	98.83±0.00	93.71±5.84	94.56±4.21	98.64±0.32	98.66±0.26	98.65±0.30	98.65±0.30
Thyr.	27.85±0.00	41.67±24.73	42.18±26.20	55.88±26.53	56.61±27.10	56.59±27.08	56.58±27.08
WDBC	98.15±0.00	97.66±0.56	97.73±0.46	96.59±0.98	96.65±0.96	96.59±1.04	96.65±0.95
Optd.	61.43±0.00	58.58±17.21	55.07±17.39	61.94±9.42	62.93±8.97	63.08±8.82	63.23±8.89
Wave.	45.64±0.00	47.40±2.99	46.98±2.28	58.05±8.63	58.34±9.29	58.33±9.29	58.33±9.29
Musk	0.17±0.00	1.66±1.25	1.30±1.13	87.11±11.80	92.10±6.95	91.65±7.61	91.30±8.22
Vowe.	87.84±0.00	84.26±5.58	83.89±6.27	75.84±8.11	75.37±8.07	75.37±8.05	75.38±8.05
Lymp.	64.11±23.78	68.52±18.19	69.25±18.62	77.14±7.82	77.15±7.80	77.05±7.96	77.15±7.80
Glass	19.95±0.00	35.64±22.97	37.99±26.57	48.71±19.15	48.54±19.54	48.61±19.54	48.60±19.52
Wilt	37.92±7.67	42.05±14.80	41.83±14.75	38.06±11.81	38.74±11.53	38.72±11.56	38.72±11.56
Lett.	57.03±0.00	57.06±0.18	57.08±0.13	53.63±2.49	53.91±2.78	53.73±2.57	53.73±2.56
Annt.	38.60±0.00	54.57±9.64	55.27±11.75	51.63±6.12	51.90±6.33	52.00±6.60	52.11±6.73
Wine	96.55±0.00	95.36±1.53	95.53±1.24	94.00±1.78	93.95±1.88	93.95±1.88	93.97±1.86
Stam.	63.43±0.00	67.81±9.13	65.82±10.29	82.82±9.54	82.93±9.48	82.94±9.48	82.94±9.47
Mnist	39.78±0.00	59.27±10.22	56.03±7.68	63.86±5.55	65.77±4.86	65.74±4.85	65.74±4.88
Page.	67.65±0.00	55.53±13.78	56.40±12.23	65.01±12.14	65.37±12.27	65.36±12.25	65.37±12.25
Vert.	31.89±0.00	39.24±14.75	40.07±14.35	34.24±12.14	34.02±12.26	34.03±12.28	34.04±12.29
Card.	53.69±0.00	59.32±6.48	60.37±8.39	67.04±7.20	67.51±6.22	67.46±6.35	67.46±6.36
WPBC	56.87±0.00	57.04±0.88	57.07±0.67	54.97±1.67	55.11±1.85	55.10±1.87	55.11±1.87
Sate.	32.22±0.00	33.09±0.59	32.85±0.41	52.64±2.56	52.35±2.33	52.46±2.35	52.44±2.34
Pima	75.42±0.00	72.84±3.15	72.16±3.55	72.46±3.95	72.71±3.65	72.71±3.63	72.70±3.64
Brea.	99.52±0.00	97.54±3.05	97.84±2.37	99.41±0.16	99.39±0.16	99.40±0.16	99.40±0.16
Iono.	25.51±0.00	26.02±0.32	25.93±0.27	69.39±8.53	69.03±8.29	69.03±8.26	69.03±8.24
Spam.	68.33±0.00	55.40±11.26	53.14±8.83	67.06±0.68	67.40±0.67	67.43±0.58	67.38±0.56
Hear.	86.03±0.00	82.70±4.38	82.86±4.31	81.64±4.95	81.94±4.89	81.95±4.89	81.95±4.87
Arrh.	52.08±0.00	51.96±0.10	52.08±0.04	71.72±2.22	71.74±1.78	71.11±2.28	71.96±2.08
Park.	83.86±0.00	80.22±5.59	80.77±4.53	60.49±8.00	60.71±8.19	60.26±7.81	60.27±7.80

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.35±0.00	0.35±0.01	0.35±0.01	0.36±0.19	0.34±0.20	0.34±0.19	0.34±0.19
Sati.	1.00±0.00	1.11±0.05	1.09±0.04	73.09±14.84	78.90±10.95	78.58±11.43	78.60±11.43
Shut.	16.10±0.00	17.95±12.91	21.86±19.13	12.29±4.38	12.25±4.53	12.22±4.60	12.19±4.62
WBC	71.51±0.00	60.83±10.86	61.94±8.90	70.73±1.34	70.85±1.20	70.78±1.18	70.79±1.22
Thyr.	2.64±0.00	6.61±7.47	6.90±6.69	9.13±7.57	9.57±7.82	9.55±7.83	9.55±7.83
WDBC	76.51±0.00	74.36±2.10	74.65±1.83	66.48±9.36	66.15±9.62	65.02±11.49	66.61±8.99
Optd.	3.92±0.00	4.17±2.86	3.57±1.84	4.05±1.62	4.11±1.53	4.12±1.49	4.15±1.53
Wave.	2.57±0.00	2.70±0.24	2.66±0.17	3.78±0.92	3.82±0.96	3.82±0.95	3.82±0.95
Musk	1.60±0.00	1.61±0.01	1.61±0.01	41.22±28.25	50.69±27.83	49.49±27.08	50.76±29.27
Vowe.	39.26±0.00	23.36±13.35	23.08±14.28	14.41±14.13	14.01±14.36	14.00±14.36	13.99±14.37
Lymp.	52.87±25.87	44.36±27.35	47.66±26.12	56.90±18.59	56.86±18.72	56.86±18.73	56.86±18.72
Glass	2.44±0.00	5.51±5.48	6.04±6.17	5.51±2.11	5.53±2.13	5.53±2.13	5.53±2.13
Wilt	3.93±0.50	4.71±1.74	4.66±1.67	4.09±0.99	4.13±0.99	4.13±1.00	4.13±1.00
Lett.	7.41±0.00	7.44±0.08	7.43±0.05	6.83±0.58	6.89±0.63	6.86±0.60	6.86±0.60
Annt.	5.68±0.00	10.70±4.13	11.26±5.15	8.31±1.55	8.45±1.77	8.49±1.87	8.52±1.90
Wine	52.47±0.00	48.42±4.90	49.16±3.75	46.15±6.38	46.06±6.85	46.06±6.85	46.08±6.83
Stam.	14.35±0.00	19.52±10.84	18.61±10.35	30.47±7.81	30.57±7.82	30.59±7.83	30.59±7.83
Mnist	10.56±0.00	20.49±6.25	18.88±5.05	21.15±3.08	22.20±2.82	22.16±2.80	22.17±2.82
Page.	31.00±0.00	29.51±11.02	30.30±10.01	33.43±8.56	32.97±8.30	32.98±8.32	32.99±8.32
Vert.	8.57±0.00	10.71±4.17	10.74±4.04	9.38±2.38	9.34±2.24	9.35±2.25	9.35±2.25
Card.	23.39±0.00	29.50±4.62	30.37±5.85	36.86±5.67	36.79±5.23	36.76±5.26	36.76±5.27
WPBC	26.17±0.00	26.26±0.61	26.26±0.52	24.81±1.07	24.88±1.12	24.89±1.16	24.91±1.19
Sate.	22.86±0.00	23.09±0.15	23.02±0.11	49.19±3.24	49.41±2.85	49.45±3.02	49.43±3.01
Pima	62.14±0.00	58.88±2.60	58.45±2.84	58.44±2.85	58.65±2.71	58.65±2.70	58.65±2.70
Brea.	99.06±0.00	96.87±3.29	97.17±2.60	98.91±0.20	98.89±0.21	98.89±0.21	98.90±0.21
Iono.	25.83±0.00	26.02±0.16	25.97±0.10	59.02±5.82	58.19±5.68	58.21±5.63	58.21±5.64
Spam.	52.54±0.00	43.91±7.81	42.02±6.47	51.14±0.75	51.54±0.70	51.58±0.60	51.53±0.58
Hear.	84.10±0.00	80.00±5.63	80.17±5.68	78.80±6.66	79.10±6.55	79.12±6.52	79.12±6.51
Arrh.	53.32±0.00	53.24±0.11	53.30±0.06	71.75±2.22	71.68±1.74	71.03±2.51	72.13±2.11
Park.	94.84±0.00	93.60±2.14	93.81±1.67	85.14±3.90	85.21±3.95	85.00±3.77	85.01±3.76

Table A30: AE(Layers=4, ReLU=yes, Bias=yes, loss=L1, scoring=L1)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	68.40±0.00	68.35±0.14	68.36±0.11	56.19±21.54	58.01±19.96	57.93±20.06	57.94±20.04
Sati.	43.38±0.00	47.28±3.15	47.08±2.69	92.59±5.60	93.50±4.76	93.53±4.75	93.52±4.76
Shut.	85.37±0.00	86.92±3.98	82.69±10.24	85.87±2.22	85.75±2.45	85.70±2.49	85.79±2.34
WBC	98.83±0.00	94.61±4.08	94.39±4.24	98.54±0.57	98.55±0.58	98.55±0.60	98.55±0.60
Thyr.	27.85±0.00	38.50±32.01	35.37±30.22	65.01±26.34	65.72±26.38	65.74±26.36	65.73±26.37
WDBC	98.15±0.00	97.75±0.33	97.78±0.23	97.07±0.75	96.97±0.90	96.97±0.89	96.97±0.89
Optd.	61.43±0.00	65.82±18.52	63.70±18.27	68.54±9.73	68.61±9.32	68.62±9.20	68.57±9.11
Wave.	45.64±0.00	46.08±0.45	46.17±0.60	60.70±14.29	60.73±14.72	60.78±14.69	60.78±14.69
Musk	0.17±0.00	1.79±0.93	0.98±0.35	60.62±25.93	59.07±23.81	59.12±23.77	59.26±23.88
Vowe.	87.84±0.00	85.92±5.88	86.50±3.91	72.51±16.14	72.32±16.19	72.27±16.16	72.27±16.16
Lymp.	55.06±31.15	68.83±22.31	67.35±23.17	69.37±23.57	69.31±23.60	69.31±23.60	69.31±23.60
Glass	19.95±0.00	30.07±14.11	30.81±14.33	44.60±20.10	43.56±19.72	43.50±19.72	43.50±19.71
Wilt	38.32±10.24	42.12±14.92	42.63±15.25	35.05±10.98	36.46±11.86	36.47±11.88	36.47±11.88
Lett.	57.03±0.00	57.11±0.18	57.09±0.13	53.54±2.41	53.25±2.01	53.25±1.99	53.26±1.99
Annt.	38.60±0.00	50.43±9.75	49.72±11.93	48.71±3.92	48.45±4.30	48.22±4.15	48.44±3.95
Wine	96.55±0.00	96.06±0.85	96.09±0.86	91.94±2.16	91.85±1.96	91.87±1.97	91.86±1.97
Stam.	63.43±0.00	57.91±8.42	59.47±10.31	66.01±13.24	66.43±12.80	66.44±12.76	66.43±12.75
Mnist	39.78±0.00	67.44±9.14	64.96±14.00	68.70±2.36	69.79±3.59	69.84±3.19	69.93±3.27
Page.	67.65±0.00	60.09±16.98	60.14±17.50	75.78±7.34	75.82±7.36	75.86±7.39	75.88±7.42
Vert.	31.89±0.00	36.13±10.14	36.02±10.36	33.14±4.78	33.29±4.43	33.29±4.44	33.29±4.44
Card.	53.69±0.00	59.30±7.40	59.24±8.09	63.47±5.11	62.26±5.27	62.35±5.27	62.34±5.30
WPBC	56.87±0.00	56.55±0.60	56.73±0.35	54.82±1.57	55.08±1.64	55.05±1.71	55.05±1.67
Sate.	32.22±0.00	32.76±0.57	32.70±0.49	51.05±3.46	50.80±3.18	50.81±3.14	50.80±3.17
Pima	75.42±0.00	74.49±5.84	74.55±6.03	76.19±2.37	75.98±2.53	75.97±2.52	75.97±2.52
Brea.	99.52±0.00	98.87±0.50	98.79±0.59	99.42±0.16	99.41±0.18	99.41±0.18	99.41±0.18
Iono.	25.51±0.00	26.33±0.63	26.19±0.56	60.55±6.53	61.32±6.95	61.12±6.87	61.12±6.88
Spam.	68.33±0.00	53.67±10.20	56.59±6.90	67.34±0.94	67.31±0.65	67.42±0.62	67.33±0.76
Hear.	86.03±0.00	82.39±5.59	82.84±5.53	80.88±4.83	81.00±4.85	81.00±4.92	81.03±4.87
Arrh.	52.08±0.00	52.08±0.02	52.08±0.01	71.82±0.68	71.71±1.87	71.82±0.92	71.09±1.40
Park.	83.86±0.00	81.51±3.17	80.98±4.08	65.08±9.73	65.47±9.82	65.44±9.84	65.44±9.82

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.35±0.00	0.35±0.00	0.35±0.00	0.42±0.39	0.44±0.42	0.44±0.42	0.44±0.42
Sati.	1.00±0.00	1.07±0.06	1.07±0.05	60.36±28.76	65.46±24.80	65.61±24.66	65.59±24.68
Shut.	16.10±0.00	17.26±5.40	13.71±5.17	13.10±3.30	13.15±3.49	13.11±3.49	13.13±3.49
WBC	71.51±0.00	64.95±7.78	65.29±7.74	71.51±1.64	71.60±1.68	71.65±1.73	71.65±1.73
Thyr.	2.64±0.00	14.34±19.51	12.39±18.84	16.64±15.52	17.04±15.62	17.04±15.63	17.04±15.63
WDBC	76.51±0.00	74.80±1.46	75.29±0.85	70.03±3.71	69.59±4.92	69.18±5.02	69.47±4.92
Optd.	3.92±0.00	5.71±3.58	5.34±3.46	4.96±1.59	4.93±1.58	4.90±1.47	4.88±1.47
Wave.	2.57±0.00	2.59±0.03	2.59±0.03	4.24±1.42	4.28±1.46	4.28±1.46	4.28±1.46
Musk	1.60±0.00	1.61±0.01	1.61±0.00	15.20±26.27	13.21±23.60	13.28±23.54	13.81±24.85
Vowe.	39.26±0.00	32.65±14.31	33.20±12.52	18.12±19.75	17.90±19.51	17.85±19.50	17.85±19.50
Lymp.	44.32±28.69	44.68±28.43	44.09±29.00	48.43±29.23	48.42±29.24	48.42±29.24	48.42±29.24
Glass	2.44±0.00	3.31±0.91	3.34±0.95	4.75±1.96	4.65±1.82	4.64±1.82	4.64±1.81
Wilt	4.04±0.86	4.65±1.92	4.71±1.93	3.91±1.06	4.02±1.11	4.02±1.11	4.02±1.11
Lett.	7.41±0.00	7.44±0.06	7.43±0.05	6.91±0.50	6.87±0.43	6.87±0.43	6.87±0.43
Annt.	5.68±0.00	8.42±2.57	8.63±3.45	7.32±0.92	7.31±1.05	7.25±0.99	7.28±0.95
Wine	52.47±0.00	50.95±2.54	51.31±2.60	40.77±8.28	40.54±8.28	40.53±8.34	40.52±8.34
Stam.	14.35±0.00	13.62±0.95	14.28±2.43	18.45±7.34	18.66±7.44	18.66±7.43	18.66±7.42
Mnist	10.56±0.00	27.68±6.80	26.59±7.94	24.05±1.69	24.79±2.49	24.71±2.21	24.78±2.23
Page.	31.00±0.00	35.33±18.57	35.05±16.40	37.32±4.79	37.84±5.00	37.87±4.94	37.89±4.94
Vert.	8.57±0.00	9.42±1.65	9.38±1.60	8.74±0.51	8.75±0.49	8.75±0.49	8.75±0.49
Card.	23.39±0.00	28.15±6.69	28.04±6.74	33.24±4.07	32.57±3.66	32.64±3.68	32.60±3.69
WPBC	26.17±0.00	25.92±0.37	26.05±0.25	24.69±0.76	24.76±0.80	24.75±0.82	24.75±0.82
Sate.	22.86±0.00	23.00±0.15	22.98±0.13	46.40±6.59	46.40±6.47	46.42±6.41	46.38±6.46
Pima	62.14±0.00	60.12±5.26	60.28±5.52	61.42±1.90	61.19±2.10	61.19±2.10	61.19±2.10
Brea.	99.06±0.00	98.33±0.58	98.28±0.63	98.99±0.14	98.97±0.18	98.97±0.18	98.97±0.18
Iono.	25.83±0.00	26.13±0.26	26.07±0.22	55.11±4.49	55.73±4.34	55.67±4.34	55.68±4.33
Spam.	52.54±0.00	42.45±7.11	44.27±5.50	51.39±0.90	51.43±0.63	51.53±0.64	51.45±0.74
Hear.	84.10±0.00	79.51±6.86	79.95±6.80	77.82±5.96	77.94±6.04	77.93±6.10	77.96±6.04
Arrh.	53.32±0.00	53.35±0.04	53.34±0.01	71.71±0.75	71.75±1.69	71.75±0.87	71.24±1.13
Park.	94.84±0.00	94.06±1.17	93.88±1.51	87.36±4.29	87.66±4.37	87.64±4.38	87.63±4.38

Table A31: AE(Layers=5, ReLU=yes, Bias=yes, loss=L1, scoring=L1)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	68.40±0.00	67.97±0.76	68.03±0.59	59.24±18.48	56.78±20.20	56.80±20.17	56.81±20.17
Sati.	43.38±0.00	48.43±1.73	47.44±1.69	91.84±6.66	93.20±5.23	93.25±5.12	93.28±5.10
Shut.	85.37±0.00	85.95±12.00	82.33±19.84	86.90±2.89	87.17±3.06	87.22±3.06	87.32±3.22
WBC	98.83±0.00	93.12±8.04	91.34±9.79	97.64±2.92	97.58±3.07	97.58±3.09	97.58±3.09
Thyr.	27.85±0.00	61.39±18.67	61.52±19.00	73.58±18.14	73.92±18.38	73.88±18.36	73.88±18.35
WDBC	98.15±0.00	97.82±0.39	97.92±0.24	97.09±0.58	97.06±0.55	97.06±0.55	97.06±0.55
Optd.	61.43±0.00	55.56±15.38	61.70±19.01	62.58±8.60	62.95±9.17	63.08±9.33	63.80±9.09
Wave.	45.64±0.00	47.26±2.07	47.35±2.82	54.58±8.34	54.98±8.16	54.96±8.16	54.96±8.16
Musk	0.17±0.00	3.06±2.24	1.32±0.64	47.98±26.88	46.12±29.83	45.67±30.06	45.69±30.01
Vowe.	87.84±0.00	87.66±3.16	88.03±2.14	75.31±10.91	74.72±10.84	74.74±10.85	74.74±10.85
Lymp.	55.06±31.15	68.83±22.31	67.35±23.17	69.37±23.57	69.31±23.60	69.31±23.60	69.31±23.60
Glass	19.95±0.00	29.73±18.41	32.35±21.71	46.74±27.62	45.07±28.20	45.07±28.22	45.06±28.20
Wilt	33.26±0.00	33.75±8.41	34.34±7.61	36.48±9.75	35.87±9.05	35.90±9.03	35.90±9.03
Lett.	57.03±0.00	57.03±0.01	57.03±0.02	53.71±2.40	53.58±2.33	53.65±2.32	53.64±2.30
Annt.	38.60±0.00	52.22±13.18	51.21±14.20	54.38±6.47	54.92±5.85	54.78±6.41	54.44±6.32
Wine	96.55±0.00	96.08±1.05	96.33±0.56	93.85±2.48	93.50±2.90	93.50±2.92	93.50±2.92
Stam.	63.43±0.00	64.47±8.28	63.82±9.85	67.78±12.29	66.60±13.50	66.62±13.52	66.62±13.51
Mnist	39.78±0.00	59.93±12.85	60.27±14.11	65.69±6.46	66.88±6.90	66.90±7.09	67.02±6.94
Page.	67.65±0.00	54.17±24.16	55.38±23.78	75.14±5.78	74.76±6.45	74.59±6.71	74.62±6.67
Vert.	31.89±0.00	37.11±9.05	37.31±8.89	32.53±10.51	32.30±10.87	32.30±10.91	32.30±10.91
Card.	53.69±0.00	61.18±5.66	61.00±5.13	67.12±5.26	65.64±5.52	65.86±5.46	65.76±5.47
WPBC	56.87±0.00	56.91±0.58	56.96±0.36	55.45±1.11	55.52±1.04	55.62±1.06	55.60±1.04
Sate.	32.22±0.00	32.84±0.33	32.65±0.25	51.95±4.92	52.67±4.38	52.55±4.26	52.55±4.26
Pima	75.42±0.00	74.95±1.36	74.52±1.96	74.28±1.26	74.03±1.36	74.03±1.37	74.03±1.37
Brea.	99.52±0.00	98.60±1.28	98.36±1.60	99.37±0.29	99.36±0.31	99.36±0.31	99.36±0.31
Iono.	25.51±0.00	26.15±0.57	26.04±0.44	64.98±7.93	65.06±8.01	64.74±8.17	64.96±8.03
Spam.	68.33±0.00	53.76±11.49	55.39±10.10	66.82±1.21	67.10±0.73	67.02±0.78	66.96±0.86
Hear.	86.03±0.00	82.45±6.26	83.17±4.82	81.89±5.78	82.01±5.33	82.07±5.19	82.02±5.31
Arrh.	52.08±0.00	52.09±0.01	52.08±0.00	72.10±1.01	71.87±0.74	72.25±0.79	72.35±0.62
Park.	83.86±0.00	82.54±1.35	82.09±1.54	65.74±5.89	64.93±6.52	64.95±6.50	64.94±6.51

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.35±0.00	0.34±0.01	0.34±0.01	0.31±0.15	0.30±0.15	0.30±0.15	0.30±0.15
Sati.	1.00±0.00	1.09±0.03	1.07±0.03	56.14±32.88	60.98±28.89	60.97±28.71	61.08±28.76
Shut.	16.10±0.00	24.25±19.21	21.75±18.04	13.19±2.40	13.51±2.33	13.57±2.40	13.65±2.45
WBC	71.51±0.00	63.48±8.67	62.97±9.48	69.85±2.11	69.66±2.26	69.64±2.30	69.66±2.30
Thyr.	2.64±0.00	17.48±19.24	16.49±18.59	22.48±23.36	22.95±23.46	22.87±23.41	22.87±23.40
WDBC	76.51±0.00	75.17±1.72	75.49±1.35	71.02±3.57	70.98±3.48	70.98±3.48	70.98±3.48
Optd.	3.92±0.00	3.56±1.64	5.31±4.13	4.07±1.40	4.19±1.54	4.23±1.61	4.32±1.67
Wave.	2.57±0.00	2.68±0.15	2.70±0.24	3.51±0.70	3.54±0.69	3.54±0.69	3.54±0.69
Musk	1.60±0.00	1.62±0.02	1.61±0.00	10.19±16.04	10.34±15.44	10.24±15.17	10.19±15.09
Vowe.	39.26±0.00	32.44±8.28	31.91±6.38	13.18±10.05	12.45±9.18	12.45±9.15	12.45±9.14
Lymp.	44.32±28.69	44.68±28.43	44.09±29.00	48.43±29.23	48.42±29.24	48.42±29.24	48.42±29.24
Glass	2.44±0.00	3.19±1.32	3.62±1.93	5.43±3.23	5.30±3.27	5.31±3.28	5.30±3.28
Wilt	3.60±0.00	3.71±0.49	3.73±0.47	3.91±0.75	3.85±0.65	3.85±0.65	3.85±0.65
Lett.	7.41±0.00	7.41±0.00	7.41±0.00	6.88±0.39	6.89±0.44	6.91±0.44	6.91±0.44
Annt.	5.68±0.00	10.04±4.62	10.34±5.63	9.29±1.99	9.41±1.94	9.40±2.03	9.31±1.99
Wine	52.47±0.00	50.92±3.00	51.52±2.01	44.69±9.20	44.08±10.22	44.06±10.25	44.06±10.25
Stam.	14.35±0.00	17.52±11.21	17.39±11.09	19.08±6.69	19.18±6.92	19.18±6.92	19.18±6.91
Mnist	10.56±0.00	23.73±8.34	23.93±9.79	22.57±3.66	23.36±4.31	23.44±4.59	23.50±4.51
Page.	31.00±0.00	32.33±21.14	32.97±21.22	35.73±6.32	35.59±6.72	35.52±6.78	35.57±6.81
Vert.	8.57±0.00	9.36±1.46	9.39±1.45	8.84±1.38	8.82±1.42	8.82±1.43	8.82±1.43
Card.	23.39±0.00	29.22±4.95	29.20±4.28	38.00±5.26	37.06±5.22	37.19±5.24	37.12±5.24
WPBC	26.17±0.00	26.04±0.35	26.12±0.14	24.81±0.50	24.87±0.44	24.93±0.47	24.92±0.45
Sate.	22.86±0.00	23.02±0.08	22.97±0.07	44.51±8.62	46.12±7.62	45.95±7.57	45.95±7.56
Pima	62.14±0.00	61.40±1.47	60.97±2.18	60.35±1.22	60.11±1.44	60.10±1.45	60.10±1.45
Brea.	99.06±0.00	98.10±1.23	97.81±1.66	98.93±0.26	98.92±0.27	98.92±0.27	98.92±0.27
Iono.	25.83±0.00	26.03±0.19	25.99±0.13	57.05±4.61	57.06±4.68	56.69±4.81	56.96±4.72
Spam.	52.54±0.00	42.52±6.74	43.24±6.26	50.86±1.13	51.19±0.70	51.06±0.72	51.02±0.83
Hear.	84.10±0.00	79.26±7.57	80.01±6.05	78.50±7.29	78.65±6.82	78.76±6.61	78.67±6.79
Arrh.	53.32±0.00	53.36±0.02	53.33±0.01	72.13±1.04	71.83±0.52	72.18±0.77	72.28±0.62
Park.	94.84±0.00	94.49±0.44	94.35±0.52	87.74±2.66	87.30±3.11	87.31±3.11	87.31±3.11

Table A32: AE(Layers=2, ReLU=yes, Bias=yes, loss=L2, scoring=L2)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	65.06±3.79	65.15±3.68	58.70±18.44	58.65±16.41	58.66±16.39	58.66±16.40
Sati.	67.11±0.00	72.70±2.23	72.45±2.14	93.44±3.89	94.07±3.69	94.04±3.68	94.04±3.68
Shut.	86.93±0.00	78.72±27.14	77.98±29.15	74.13±22.78	73.51±23.72	73.77±23.48	73.76±23.50
WBC	98.65±0.00	85.30±17.37	84.52±18.01	97.62±2.51	97.56±2.63	97.56±2.63	97.56±2.63
Thyr.	51.75±16.09	74.71±24.83	73.71±25.94	66.32±25.33	66.80±25.59	66.82±25.59	66.82±25.59
WDBC	97.68±0.00	97.22±0.57	97.19±0.50	95.64±1.30	95.63±1.34	95.64±1.36	95.64±1.36
Optd.	59.10±0.00	49.21±19.74	50.34±17.39	53.40±15.94	53.66±15.69	53.64±15.63	53.57±15.56
Wave.	51.22±0.00	56.66±8.32	56.02±7.95	57.27±13.88	56.50±14.48	56.49±14.47	56.49±14.47
Musk	11.94±0.00	22.46±5.66	17.63±2.87	79.68±15.60	82.36±15.01	82.12±15.23	82.10±15.21
Vowe.	90.15±0.00	80.95±8.06	81.52±8.03	65.27±15.34	64.70±15.71	64.71±15.71	64.70±15.71
Lymp.	55.34±31.95	62.98±26.74	61.65±27.33	67.38±25.37	66.76±25.49	66.71±25.44	66.71±25.44
Glass	26.88±13.60	31.65±13.68	31.18±13.19	42.99±20.18	43.76±20.27	43.79±20.25	43.79±20.24
Wilt	39.47±8.13	40.43±10.08	40.22±10.48	39.29±7.51	39.34±7.22	39.36±7.24	39.36±7.24
Lett.	56.33±0.00	55.79±0.80	55.79±0.75	52.75±3.51	53.08±3.82	53.02±3.79	53.03±3.79
Annt.	44.18±0.00	58.68±9.33	59.36±9.35	51.39±7.49	48.55±6.93	48.53±6.97	48.53±6.97
Wine	95.80±0.00	93.29±2.47	93.50±2.42	87.24±7.58	86.42±9.16	86.34±9.34	86.34±9.34
Stam.	66.81±0.00	65.16±14.80	65.41±14.80	62.12±16.89	62.02±16.93	62.00±16.96	62.00±16.96
Mnist	58.28±0.00	76.04±8.82	76.77±8.68	69.48±4.95	69.46±5.21	69.41±5.03	69.37±5.08
Page.	70.92±0.00	41.65±12.59	42.12±13.48	50.55±14.03	50.19±13.93	50.15±13.94	50.16±13.94
Vert.	35.04±6.00	34.44±12.88	33.73±11.62	31.78±7.28	31.78±7.55	31.78±7.55	31.77±7.54
Card.	60.06±0.00	62.02±8.09	61.54±7.61	66.42±10.35	66.30±10.36	66.29±10.36	66.29±10.36
WPBC	56.47±0.00	55.53±0.72	55.55±0.76	54.25±2.13	54.45±2.08	54.62±2.17	54.45±2.07
Sate.	38.03±0.00	39.75±0.82	39.64±0.76	49.43±3.18	49.37±3.08	49.41±3.06	49.41±3.06
Pima	76.08±0.00	74.13±2.73	74.33±2.75	73.51±3.78	73.51±3.80	73.51±3.79	73.51±3.79
Brea.	99.53±0.00	93.91±8.23	95.01±5.51	98.54±0.87	98.52±0.93	98.51±0.93	98.51±0.93
Iono.	32.83±0.00	33.98±0.74	33.95±0.77	51.08±4.80	51.26±4.87	51.25±4.87	51.52±4.68
Spam.	60.31±0.00	42.00±8.29	42.67±8.78	57.89±1.80	57.85±1.67	57.94±1.72	57.94±1.72
Hear.	85.21±0.00	82.90±2.02	83.49±2.02	79.52±5.44	78.64±5.20	78.65±5.22	78.65±5.22
Arrh.	55.38±0.00	55.34±0.43	55.29±0.47	59.25±4.20	59.64±4.40	60.13±4.37	59.74±3.84
Park.	79.08±0.00	75.59±4.36	75.96±3.43	65.27±8.85	65.36±8.83	65.38±8.77	65.39±8.78

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.34±0.07	0.34±0.06	0.30±0.20	0.29±0.20	0.29±0.20	0.29±0.20
Sati.	1.89±0.00	3.99±1.82	3.75±1.39	65.13±21.61	68.84±19.14	68.68±19.14	68.68±19.14
Shut.	17.14±0.00	16.94±12.71	17.29±12.81	13.19±10.87	12.98±10.52	12.99±10.51	12.99±10.51
WBC	70.28±0.00	51.08±16.83	52.06±15.14	66.64±6.44	66.77±6.43	66.77±6.41	66.77±6.41
Thyr.	16.99±20.81	32.30±23.82	32.90±25.31	24.41±18.80	25.19±19.60	25.20±19.62	25.21±19.63
WDBC	70.66±0.00	66.88±3.17	66.93±3.25	59.28±10.29	59.24±11.00	59.38±11.21	59.46±11.25
Optd.	3.41±0.00	3.23±1.75	3.10±1.55	3.24±1.26	3.25±1.24	3.24±1.24	3.24±1.24
Wave.	2.88±0.00	3.52±0.94	3.45±0.90	3.87±1.43	3.84±1.49	3.84±1.48	3.84±1.48
Musk	1.72±0.00	2.81±1.25	2.19±0.45	41.34±24.49	44.56±21.96	45.15±23.64	45.11±23.59
Vowe.	39.78±0.00	21.51±16.16	22.34±16.59	12.22±14.59	12.00±14.39	12.00±14.40	12.00±14.40
Lymp.	43.92±27.87	45.32±28.11	45.21±28.14	46.21±28.03	46.56±28.52	46.12±28.17	46.12±28.17
Glass	3.37±1.90	3.12±0.77	3.07±0.70	4.22±1.78	4.23±1.75	4.23±1.75	4.23±1.75
Wilt	4.06±0.63	4.17±0.78	4.17±0.88	4.02±0.49	4.01±0.45	4.02±0.45	4.02±0.45
Lett.	7.42±0.00	7.33±0.17	7.32±0.15	7.14±1.21	7.30±1.31	7.29±1.30	7.29±1.30
Annt.	7.43±0.00	13.16±6.01	13.20±5.66	9.12±1.57	8.45±1.39	8.45±1.40	8.45±1.40
Wine	49.35±0.00	41.68±7.30	42.32±7.06	32.86±17.49	32.38±17.65	32.36±17.68	32.36±17.68
Stam.	15.64±0.00	17.00±5.38	17.04±5.48	16.72±7.84	16.61±7.71	16.60±7.71	16.61±7.71
Mnist	22.31±0.00	34.27±10.91	34.53±9.72	28.30±2.37	28.47±2.38	28.41±2.34	28.39±2.36
Page.	35.38±0.00	24.09±10.86	23.80±11.68	28.87±12.49	28.96±12.16	28.95±12.15	28.95±12.14
Vert.	9.08±0.96	9.38±2.17	9.18±1.85	8.65±0.84	8.67±0.89	8.67±0.89	8.67±0.89
Card.	28.82±0.00	33.04±4.22	32.64±3.86	38.40±9.02	38.15±8.86	38.14±8.85	38.14±8.85
WPBC	25.68±0.00	25.09±0.44	25.10±0.47	24.90±1.74	25.07±1.75	25.14±1.72	25.07±1.74
Sate.	24.44±0.00	25.38±0.61	25.30±0.47	42.85±7.89	42.94±8.17	43.12±8.20	43.12±8.21
Pima	61.69±0.00	59.13±2.69	59.33±2.63	57.82±4.08	57.86±4.10	57.86±4.09	57.86±4.09
Brea.	99.11±0.00	93.71±7.46	94.70±5.05	97.66±1.19	97.63±1.26	97.62±1.27	97.62±1.27
Iono.	30.87±0.00	31.86±0.52	31.86±0.52	51.28±4.82	51.27±4.84	51.26±4.82	51.31±4.82
Spam.	44.11±0.00	35.74±3.96	35.98±4.26	42.63±1.17	42.62±1.05	42.67±1.09	42.67±1.09
Hear.	81.29±0.00	78.06±2.43	78.72±2.33	73.33±5.75	72.13±6.07	72.14±6.09	72.15±6.09
Arrh.	56.00±0.00	56.25±0.31	55.97±0.38	60.11±4.06	60.75±4.20	61.13±4.25	60.83±3.83
Park.	93.37±0.00	91.86±1.65	92.07±1.22	86.98±4.24	87.08±4.26	87.10±4.24	87.10±4.24

Table A33: AE(Layers=3, ReLU=yes, Bias=yes, loss=L2, scoring=L2)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	66.42±7.07	66.77±6.61	61.21±17.19	60.31±17.51	60.30±17.51	60.30±17.51
Sati.	67.11±0.00	71.08±2.06	70.53±1.97	90.14±5.79	90.22±5.80	90.21±5.80	90.22±5.80
Shut.	86.93±0.00	75.36±36.85	75.88±35.57	76.82±26.15	75.43±26.77	75.42±26.78	75.42±26.79
WBC	98.65±0.00	88.80±15.07	90.48±10.36	97.69±2.35	97.70±1.99	97.69±2.02	97.69±2.02
Thyr.	45.04±0.00	55.07±21.60	52.10±22.64	55.63±22.72	54.82±22.41	54.80±22.40	54.80±22.40
WDBC	97.68±0.00	97.24±0.73	97.27±0.59	96.72±0.79	96.57±0.85	96.57±0.84	96.57±0.85
Optd.	59.10±0.00	55.65±13.60	53.62±14.81	54.59±11.73	54.52±12.11	54.93±11.59	54.85±11.66
Wave.	51.22±0.00	54.12±5.72	53.26±5.16	54.07±13.28	54.13±13.23	54.12±13.23	54.10±13.25
Musk	11.94±0.00	18.29±5.04	16.80±3.91	68.37±11.28	72.96±11.32	72.14±11.09	72.36±10.92
Vowe.	90.15±0.00	84.30±4.81	84.19±5.17	78.62±9.14	78.62±8.95	78.62±8.95	78.62±8.95
Lymp.	69.41±17.77	72.01±17.17	71.31±17.35	75.45±14.99	75.41±15.22	75.41±15.22	75.41±15.22
Glass	20.22±0.00	37.44±22.89	36.35±23.80	37.54±20.47	37.18±19.85	37.18±19.86	37.18±19.87
Wilt	41.08±11.68	41.01±15.60	40.18±15.57	41.16±14.45	41.21±14.22	41.22±14.21	41.22±14.21
Lett.	56.33±0.00	56.56±0.50	56.59±0.58	54.68±4.34	54.65±4.41	54.58±4.52	54.58±4.52
Annt.	44.18±0.00	59.81±13.80	60.78±12.64	54.04±12.21	51.89±11.07	51.97±11.02	51.98±11.02
Wine	95.80±0.00	93.72±2.66	93.86±2.39	91.32±4.81	91.35±5.07	91.35±5.07	91.34±5.07
Stam.	66.81±0.00	71.61±10.23	69.92±10.75	76.62±9.26	76.23±9.32	76.23±9.33	76.23±9.33
Mnist	58.28±0.00	77.55±4.51	76.48±6.46	68.26±2.01	67.96±2.31	68.08±2.29	68.10±2.32
Page.	70.92±0.00	53.12±14.98	53.74±14.37	62.45±14.55	62.13±14.16	62.15±14.17	62.15±14.17
Vert.	31.62±0.00	35.78±12.44	36.37±12.46	32.19±12.87	32.33±12.73	32.32±12.73	32.32±12.73
Card.	60.06±0.00	65.36±7.19	65.69±7.68	63.21±7.88	61.33±7.48	61.33±7.46	61.33±7.46
WPBC	56.47±0.00	56.32±0.64	56.38±0.66	55.29±2.09	55.03±2.22	55.04±2.23	55.02±2.23
Sate.	38.03±0.00	39.22±0.77	39.04±0.74	46.54±3.78	46.81±3.50	46.84±3.54	46.82±3.52
Pima	76.08±0.00	73.84±3.15	73.66±3.21	71.96±4.78	72.02±4.84	72.02±4.84	72.02±4.84
Brea.	99.53±0.00	95.92±5.47	96.50±4.35	98.91±0.66	98.88±0.73	98.88±0.73	98.88±0.73
Iono.	32.83±0.00	33.85±0.48	33.79±0.50	54.09±6.40	53.91±6.58	53.89±6.57	53.89±6.58
Spam.	60.31±0.00	43.24±10.50	40.50±9.74	58.77±0.99	58.75±1.17	58.90±1.26	58.96±1.20
Hear.	85.21±0.00	82.88±2.81	82.99±2.85	80.82±5.86	80.99±5.90	80.99±5.89	80.99±5.89
Arrh.	55.38±0.00	55.48±0.27	55.51±0.19	59.74±5.15	59.85±4.71	59.99±4.47	60.00±4.66
Park.	79.08±0.00	75.60±5.47	75.89±5.48	65.74±11.16	65.73±11.27	65.74±11.29	65.74±11.30

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.50±0.43	0.87±1.53	0.92±1.60	0.91±1.61	0.91±1.61	0.91±1.61
Sati.	1.89±0.00	2.79±0.55	2.58±0.43	51.09±23.25	51.87±22.14	51.61±22.11	51.65±22.12
Shut.	17.14±0.00	25.01±21.07	23.70±17.64	20.96±19.10	20.82±19.64	20.83±19.67	20.83±19.67
WBC	70.28±0.00	56.81±16.36	56.85±15.26	68.46±2.02	68.21±2.58	68.15±2.67	68.15±2.67
Thyr.	10.10±0.00	12.59±8.29	11.69±7.88	13.31±7.93	13.28±8.37	13.28±8.37	13.28±8.37
WDBC	70.66±0.00	68.65±3.98	68.17±3.44	64.39±6.22	63.33±6.67	63.33±6.67	63.33±6.68
Optd.	3.41±0.00	3.30±1.17	3.10±0.95	3.22±1.14	3.23±1.15	3.25±1.15	3.24±1.13
Wave.	2.88±0.00	3.18±0.52	3.10±0.45	3.52±1.24	3.49±1.17	3.49±1.17	3.49±1.17
Musk	1.72±0.00	3.28±1.10	2.40±0.65	22.98±10.49	26.59±14.00	25.32±12.55	25.14±12.54
Vowe.	39.78±0.00	22.70±11.86	22.73±12.17	18.29±14.45	18.14±14.37	18.14±14.37	18.14±14.37
Lymp.	51.51±22.64	46.72±24.03	47.59±23.51	56.63±18.25	56.76±18.50	56.76±18.50	56.76±18.50
Glass	2.45±0.00	4.55±2.75	4.39±2.80	4.36±1.88	4.32±1.80	4.32±1.81	4.32±1.81
Wilt	4.26±0.89	4.69±2.05	4.60±1.96	4.57±1.82	4.56±1.77	4.56±1.77	4.56±1.77
Lett.	7.42±0.00	7.53±0.11	7.54±0.17	7.42±1.16	7.40±1.22	7.40±1.23	7.40±1.23
Annt.	7.43±0.00	16.06±8.41	16.09±8.78	10.43±3.47	9.62±2.99	9.65±3.01	9.65±3.01
Wine	49.35±0.00	43.19±8.41	43.56±7.68	39.38±12.59	39.73±13.18	39.73±13.18	39.64±13.11
Stam.	15.64±0.00	20.31±6.93	19.40±7.14	23.43±7.47	23.24±7.75	23.25±7.76	23.25±7.76
Mnist	22.31±0.00	34.08±6.75	33.61±7.99	27.74±1.43	27.47±1.68	27.53±1.63	27.54±1.65
Page.	35.38±0.00	29.10±12.15	29.63±11.17	35.94±11.39	36.69±11.81	36.70±11.80	36.70±11.80
Vert.	8.56±0.00	9.84±3.43	10.02±3.82	9.20±2.80	9.22±2.84	9.22±2.84	9.22±2.84
Card.	28.82±0.00	34.56±6.05	35.09±6.10	34.13±5.24	33.01±3.48	33.01±3.47	33.01±3.47
WPBC	25.68±0.00	25.62±0.44	25.67±0.41	25.35±1.69	25.19±1.78	25.19±1.78	25.18±1.79
Sate.	24.44±0.00	25.03±0.37	24.93±0.34	38.59±7.48	38.68±6.92	38.69±7.06	38.64±7.05
Pima	61.69±0.00	59.07±2.63	59.01±2.65	57.18±4.11	57.20±4.06	57.20±4.06	57.20±4.06
Brea.	99.11±0.00	95.57±5.09	96.00±4.25	98.37±0.66	98.34±0.72	98.34±0.73	98.34±0.73
Iono.	30.87±0.00	31.66±0.33	31.58±0.33	50.29±5.58	50.58±5.96	50.56±5.95	50.56±5.95
Spam.	44.11±0.00	36.21±5.19	34.85±4.38	43.19±0.70	43.19±0.87	43.28±0.93	43.32±0.90
Hear.	81.29±0.00	78.49±3.88	78.56±3.96	75.99±7.46	76.30±7.47	76.31±7.46	76.31±7.46
Arrh.	56.00±0.00	56.12±0.23	56.11±0.13	59.95±4.64	60.10±4.31	60.23±4.10	60.22±4.21
Park.	93.37±0.00	91.93±2.32	92.01±2.27	86.80±5.34	86.81±5.43	86.82±5.44	86.81±5.45

Table A34: AE(Layers=4, ReLU=yes, Bias=yes, loss=L2, scoring=L2)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	66.94±6.47	66.10±7.34	57.81±22.17	57.40±22.29	57.53±22.22	57.53±22.22
Sati.	67.11±0.00	69.75±2.40	70.18±2.02	86.91±6.68	87.55±6.67	87.53±6.67	87.53±6.67
Shut.	86.93±0.00	80.65±10.57	78.63±14.55	75.00±19.82	75.45±19.54	75.43±19.54	75.43±19.54
WBC	98.65±0.00	92.92±5.26	92.36±6.36	98.41±0.25	98.39±0.28	98.39±0.29	98.39±0.29
Thyr.	45.04±0.00	48.62±35.54	48.12±35.96	53.42±28.87	53.14±29.35	53.11±29.36	53.11±29.36
WDBC	97.68±0.00	97.35±0.38	97.34±0.32	96.65±0.96	96.43±1.05	96.45±1.05	96.45±1.05
Optd.	59.10±0.00	63.84±15.71	62.54±17.23	62.76±8.34	62.56±8.30	62.67±8.16	62.66±8.17
Wave.	51.22±0.00	54.34±4.44	53.86±4.58	59.25±15.05	59.23±15.18	59.21±15.19	59.21±15.19
Musk	11.94±0.00	17.18±3.63	15.72±3.53	63.68±19.86	64.21±18.91	64.06±18.62	63.97±18.58
Vowe.	90.15±0.00	83.83±10.76	84.16±10.51	73.64±17.51	73.65±17.76	73.64±17.77	73.64±17.77
Lymp.	55.34±31.95	62.98±26.74	61.65±27.33	67.38±25.37	66.76±25.49	66.71±25.44	66.71±25.44
Glass	20.22±0.00	29.39±17.74	29.10±16.97	32.41±16.17	31.76±16.16	31.75±16.16	31.75±16.16
Wilt	39.87±14.27	41.10±14.94	41.48±14.68	37.65±10.93	37.45±10.77	37.46±10.77	37.45±10.78
Lett.	56.33±0.00	56.15±0.84	56.10±0.81	54.06±3.05	54.15±2.53	54.16±2.53	54.15±2.53
Annt.	44.18±0.00	55.89±11.15	55.42±13.24	48.12±9.67	48.84±8.41	48.98±8.47	48.98±8.46
Wine	95.80±0.00	94.63±1.39	94.50±1.40	91.18±4.20	91.06±4.44	91.04±4.46	91.06±4.46
Stam.	66.81±0.00	60.77±12.51	61.01±12.72	57.69±19.75	58.60±19.00	58.61±19.00	58.61±18.99
Mnist	58.28±0.00	80.45±8.75	79.45±11.04	67.92±3.98	68.81±4.11	68.39±4.06	68.38±4.06
Page.	70.92±0.00	58.90±18.05	58.82±16.78	70.12±10.77	67.83±12.08	67.86±12.07	67.86±12.07
Vert.	31.62±0.00	35.22±9.39	34.61±9.62	33.80±5.95	33.84±5.66	33.84±5.67	33.84±5.67
Card.	60.06±0.00	62.63±7.84	62.80±8.52	60.82±9.16	61.17±9.13	61.16±9.13	61.16±9.14
WPBC	56.47±0.00	56.10±0.62	56.20±0.70	55.32±2.37	55.44±2.38	55.35±2.47	55.37±2.45
Sate.	38.03±0.00	38.70±0.91	38.86±0.77	46.19±3.38	44.74±4.38	44.72±4.38	44.73±4.38
Pima	76.08±0.00	76.13±4.15	76.00±4.15	76.37±3.10	76.35±3.01	76.35±3.01	76.35±3.01
Brea.	99.53±0.00	98.81±0.38	98.73±0.49	99.07±0.29	99.05±0.32	99.05±0.32	99.05±0.32
Iono.	32.83±0.00	33.98±1.01	33.84±0.91	47.10±3.77	47.54±4.19	47.70±3.98	47.70±3.99
Spam.	60.31±0.00	44.44±8.72	44.32±5.75	58.57±1.63	58.51±1.85	58.47±1.87	58.47±1.87
Hear.	85.21±0.00	82.53±4.79	82.40±4.87	80.23±3.79	80.30±3.54	80.30±3.54	80.30±3.54
Arrh.	55.38±0.00	55.41±0.27	55.45±0.18	58.69±2.51	58.69±2.59	58.99±2.42	59.09±2.55
Park.	79.08±0.00	77.24±3.57	77.00±4.17	71.43±9.52	70.73±9.90	70.77±9.89	70.77±9.89

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.37±0.09	0.36±0.09	0.45±0.41	0.44±0.41	0.44±0.41	0.44±0.41
Sati.	1.89±0.00	2.57±1.05	2.75±1.08	39.60±24.10	41.58±23.83	41.54±23.83	41.54±23.84
Shut.	17.14±0.00	14.93±6.50	14.51±6.81	13.91±9.48	13.88±9.50	13.88±9.50	13.88±9.49
WBC	70.28±0.00	60.31±6.56	59.72±6.62	68.50±1.34	68.40±1.74	68.43±1.77	68.43±1.77
Thyr.	10.10±0.00	21.58±26.11	20.16±24.41	16.88±15.52	17.73±17.04	17.72±17.05	17.72±17.05
WDBC	70.66±0.00	67.83±2.28	67.71±2.00	63.48±8.33	62.47±8.50	62.52±8.42	62.52±8.42
Optd.	3.41±0.00	4.73±2.90	4.47±2.41	3.80±0.94	3.78±0.94	3.79±0.93	3.79±0.93
Wave.	2.88±0.00	3.18±0.36	3.14±0.37	4.17±1.48	4.17±1.46	4.17±1.46	4.17±1.46
Musk	1.72±0.00	2.26±0.50	1.97±0.24	22.78±17.16	21.51±15.32	22.14±16.06	22.04±16.08
Vowe.	39.78±0.00	31.08±20.16	31.73±18.91	23.19±25.02	23.16±25.05	23.16±25.05	23.16±25.05
Lymp.	43.92±27.87	45.32±28.11	45.21±28.14	46.21±28.03	46.56±28.52	46.12±28.17	46.12±28.17
Glass	2.45±0.00	3.34±1.53	3.31±1.43	3.34±1.05	3.34±1.12	3.34±1.12	3.34±1.12
Wilt	4.41±1.61	4.54±1.75	4.56±1.77	4.03±0.92	4.02±0.95	4.02±0.95	4.02±0.95
Lett.	7.42±0.00	7.42±0.22	7.40±0.22	7.14±0.72	7.14±0.71	7.14±0.71	7.14±0.71
Annt.	7.43±0.00	11.24±4.24	11.90±5.61	8.67±1.98	8.70±1.67	8.72±1.67	8.72±1.67
Wine	49.35±0.00	45.28±4.34	45.58±5.75	36.32±11.50	36.11±11.70	36.08±11.72	36.11±11.71
Stam.	15.64±0.00	15.88±3.87	15.89±4.04	16.09±6.45	15.95±6.59	15.96±6.60	15.96±6.60
Mnist	22.31±0.00	40.27±7.86	39.84±8.72	27.43±2.44	27.92±2.51	27.64±2.48	27.63±2.48
Page.	35.38±0.00	38.45±19.03	37.20±16.18	39.25±10.78	38.06±10.53	38.06±10.54	38.06±10.54
Vert.	8.56±0.00	9.26±1.44	9.15±1.29	8.86±0.64	8.86±0.61	8.86±0.61	8.86±0.61
Card.	28.82±0.00	32.23±6.25	32.49±6.89	32.67±6.73	32.93±6.64	32.93±6.64	32.93±6.64
WPBC	25.68±0.00	25.53±0.52	25.57±0.55	25.44±1.38	25.52±1.34	25.43±1.42	25.45±1.42
Sate.	24.44±0.00	24.79±0.49	24.86±0.42	37.85±6.37	35.96±7.42	35.93±7.42	35.95±7.42
Pima	61.69±0.00	60.94±3.28	60.90±3.27	60.78±3.94	60.75±3.85	60.75±3.84	60.76±3.84
Brea.	99.11±0.00	98.18±0.48	98.10±0.56	98.49±0.34	98.47±0.37	98.47±0.37	98.47±0.37
Iono.	30.87±0.00	31.73±0.35	31.65±0.31	46.80±3.20	47.48±4.04	47.66±3.84	47.66±3.84
Spam.	44.11±0.00	36.77±4.29	36.50±2.75	42.99±1.07	42.96±1.25	42.93±1.27	42.93±1.27
Hear.	81.29±0.00	77.96±5.43	77.75±5.26	74.09±4.92	74.08±4.60	74.07±4.59	74.07±4.59
Arrh.	56.00±0.00	56.11±0.24	56.10±0.18	59.79±2.38	59.76±2.45	59.95±2.27	60.01±2.33
Park.	93.37±0.00	92.63±1.32	92.50±1.57	89.90±4.14	89.54±4.36	89.55±4.36	89.55±4.36

Table A35: AE(Layers=5, ReLU=yes, Bias=yes, loss=L2, scoring=L2)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	64.36±5.31	65.14±4.60	55.92±15.28	55.88±15.13	55.86±15.16	55.87±15.14
Sati.	67.11±0.00	70.52±1.43	69.88±1.35	87.11±7.15	86.63±8.02	86.62±8.06	86.64±8.06
Shut.	86.93±0.00	84.29±17.71	82.04±20.06	82.63±15.35	82.84±14.63	82.82±14.64	82.82±14.64
WBC	98.65±0.00	92.02±7.62	89.97±10.56	97.45±2.97	97.41±2.99	97.41±2.99	97.41±2.99
Thyr.	45.04±0.00	83.19±9.30	82.39±10.62	76.30±15.66	76.12±16.65	76.13±16.65	76.13±16.65
WDBC	97.68±0.00	97.53±0.20	97.43±0.27	96.58±0.94	96.55±0.93	96.55±0.93	96.55±0.93
Optd.	59.10±0.00	52.73±16.44	57.39±18.85	58.42±7.59	58.40±7.13	58.44±7.11	58.44±7.11
Wave.	51.22±0.00	53.43±4.10	53.23±4.79	48.80±11.35	48.68±11.48	48.64±11.50	48.67±11.48
Musk	11.94±0.00	20.61±5.02	18.05±2.91	57.26±18.53	57.39±17.54	56.95±17.66	56.95±17.66
Vowe.	90.15±0.00	87.75±5.06	87.40±5.28	73.89±12.13	74.11±12.48	74.11±12.47	74.11±12.47
Lymp.	55.34±31.95	62.98±26.74	61.65±27.33	67.38±25.37	66.76±25.49	66.71±25.44	66.71±25.44
Glass	20.22±0.00	32.48±21.19	31.38±22.78	39.39±27.38	38.53±27.38	38.53±27.38	38.53±27.38
Wilt	32.45±0.00	35.51±9.59	34.85±9.64	36.23±10.12	36.40±10.19	36.40±10.20	36.40±10.20
Lett.	56.33±0.00	55.94±0.47	56.00±0.51	54.50±3.06	54.40±3.08	54.40±3.08	54.40±3.08
Annt.	44.18±0.00	61.56±11.57	59.32±11.84	52.00±12.07	49.66±11.14	49.65±11.12	49.65±11.12
Wine	95.80±0.00	94.82±1.85	94.84±1.46	92.01±3.60	92.13±3.55	92.12±3.55	92.12±3.55
Stam.	66.81±0.00	64.17±11.21	63.89±11.06	59.78±19.57	59.83±19.52	59.84±19.51	59.84±19.51
Mnist	58.28±0.00	73.06±11.73	74.52±10.82	68.13±4.66	68.11±4.86	68.19±4.90	68.20±4.90
Page.	70.92±0.00	50.58±19.18	52.75±17.68	69.94±10.35	70.44±10.06	70.40±10.09	70.40±10.09
Vert.	31.62±0.00	35.30±8.55	35.45±9.04	29.97±6.76	30.15±7.24	30.14±7.24	30.14±7.24
Card.	60.06±0.00	63.80±6.20	63.59±5.52	63.68±9.76	64.04±10.28	64.03±10.28	64.03±10.28
WPBC	56.47±0.00	56.21±0.89	56.20±0.75	55.79±1.49	55.86±1.54	55.86±1.54	55.86±1.54
Sate.	38.03±0.00	39.03±0.47	38.82±0.45	45.85±3.77	45.77±4.13	45.74±4.13	45.74±4.13
Pima	76.08±0.00	75.22±1.06	74.97±1.19	73.98±2.10	74.03±2.07	74.03±2.07	74.03±2.07
Brea.	99.53±0.00	98.69±0.92	98.40±1.50	99.00±0.56	99.01±0.53	99.01±0.53	99.01±0.53
Iono.	32.83±0.00	34.08±0.91	34.03±0.84	50.68±6.88	50.99±6.71	51.53±7.36	51.53±7.36
Spam.	60.31±0.00	44.13±8.96	43.13±9.11	59.36±2.08	59.17±1.99	59.15±1.99	59.15±1.99
Hear.	85.21±0.00	81.53±4.69	81.71±3.97	78.69±5.03	78.85±4.76	78.86±4.76	78.87±4.76
Arrh.	55.38±0.00	55.54±0.12	55.51±0.13	60.71±2.46	60.43±1.83	60.57±2.19	60.37±2.42
Park.	79.08±0.00	77.08±2.28	76.86±2.12	69.18±6.84	68.65±6.76	68.64±6.76	68.63±6.76

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.41±0.26	0.36±0.12	0.28±0.15	0.27±0.15	0.27±0.15	0.27±0.15
Sati.	1.89±0.00	2.53±0.39	2.37±0.33	38.88±26.65	38.59±27.01	38.60±27.05	38.63±27.03
Shut.	17.14±0.00	21.34±11.95	18.52±8.66	19.02±12.83	18.19±12.00	18.18±11.98	18.18±11.98
WBC	70.28±0.00	59.28±11.61	58.37±12.62	67.82±3.03	67.19±4.25	67.19±4.25	67.19±4.25
Thyr.	10.10±0.00	30.69±15.10	30.88±16.85	27.43±17.73	28.11±18.10	28.12±18.11	28.12±18.12
WDBC	70.66±0.00	68.36±1.89	68.10±1.86	64.18±2.97	64.01±3.01	64.01±3.01	64.01±3.01
Optd.	3.41±0.00	3.25±1.58	4.22±3.25	3.39±0.76	3.37±0.75	3.38±0.75	3.38±0.75
Wave.	2.88±0.00	3.11±0.38	3.10±0.45	2.99±0.78	2.98±0.79	2.98±0.79	2.98±0.79
Musk	1.72±0.00	2.84±1.20	2.08±0.35	16.00±16.64	15.25±15.95	15.13±16.00	15.12±16.00
Vowe.	39.78±0.00	29.12±13.38	29.60±12.67	15.66±16.31	15.84±16.64	15.83±16.63	15.83±16.64
Lymp.	43.92±27.87	45.32±28.11	45.21±28.14	46.21±28.03	46.56±28.52	46.12±28.17	46.12±28.17
Glass	2.45±0.00	3.52±1.70	3.61±1.97	4.51±2.74	4.41±2.63	4.41±2.63	4.41±2.63
Wilt	3.57±0.00	3.85±0.70	3.82±0.76	3.92±0.85	3.93±0.85	3.93±0.85	3.93±0.85
Lett.	7.42±0.00	7.41±0.10	7.43±0.12	7.30±0.76	7.26±0.75	7.26±0.75	7.26±0.75
Annt.	7.43±0.00	14.84±6.88	13.81±7.06	9.54±2.77	8.92±2.35	8.92±2.34	8.92±2.34
Wine	49.35±0.00	47.27±5.74	46.64±4.61	39.32±10.49	39.72±10.50	39.63±10.48	39.63±10.48
Stam.	15.64±0.00	18.33±7.71	18.14±7.00	17.92±9.54	17.91±9.46	17.92±9.46	17.92±9.46
Mnist	22.31±0.00	33.96±10.47	35.13±10.46	27.53±2.59	27.56±2.70	27.60±2.73	27.61±2.73
Page.	35.38±0.00	26.70±15.63	27.64±15.42	38.22±13.68	39.04±13.98	39.02±14.00	39.02±14.00
Vert.	8.56±0.00	9.07±1.14	9.11±1.22	8.40±0.68	8.43±0.74	8.43±0.74	8.43±0.74
Card.	28.82±0.00	32.32±4.37	32.15±3.87	35.83±7.53	35.89±8.00	35.87±7.99	35.87±7.99
WPBC	25.68±0.00	25.48±0.69	25.47±0.60	25.30±0.89	25.32±0.87	25.32±0.87	25.33±0.87
Sate.	24.44±0.00	24.90±0.24	24.79±0.22	35.46±7.95	35.80±8.30	35.73±8.34	35.73±8.34
Pima	61.69±0.00	60.68±0.85	60.41±1.02	59.46±2.13	59.39±2.24	59.39±2.23	59.39±2.23
Brea.	99.11±0.00	98.09±0.98	97.81±1.51	98.45±0.52	98.46±0.50	98.45±0.50	98.45±0.50
Iono.	30.87±0.00	31.63±0.39	31.62±0.32	47.56±3.82	47.60±3.87	48.04±4.73	48.03±4.73
Spam.	44.11±0.00	36.57±3.99	36.04±3.99	43.51±1.32	43.39±1.25	43.37±1.25	43.37±1.25
Hear.	81.29±0.00	76.11±5.58	76.39±4.79	72.39±6.40	72.54±6.16	72.57±6.12	72.57±6.13
Arrh.	56.00±0.00	56.20±0.15	56.13±0.08	61.67±2.33	61.30±1.92	61.38±2.18	61.22±2.39
Park.	93.37±0.00	92.61±0.84	92.54±0.81	88.98±3.38	88.73±3.31	88.72±3.31	88.72±3.31

Table A36: AE(Layers=2, ReLU=yes, Bias=yes, loss=SL1, scoring=SL1)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	65.06±3.79	65.15±3.68	58.71±18.44	58.65±16.40	58.66±16.40	58.66±16.40
Sati.	67.11±0.00	72.70±2.23	72.45±2.14	93.46±3.89	94.09±3.70	94.05±3.69	94.05±3.69
Shut.	86.93±0.00	78.72±27.14	77.98±29.15	74.13±22.79	73.52±23.71	73.77±23.49	73.78±23.48
WBC	98.65±0.00	85.30±17.37	84.52±18.01	97.62±2.51	97.56±2.63	97.56±2.63	97.56±2.63
Thyr.	51.75±16.09	74.71±24.83	73.71±25.94	66.32±25.33	66.80±25.59	66.82±25.59	66.82±25.59
WDBC	97.68±0.00	97.22±0.57	97.19±0.50	95.66±1.29	95.64±1.35	95.64±1.36	95.65±1.36
Optd.	59.10±0.00	49.21±19.74	50.34±17.39	53.91±16.02	53.98±15.85	53.89±15.77	53.90±15.76
Wave.	51.22±0.00	56.66±8.32	56.02±7.95	57.59±13.43	56.45±14.55	56.32±14.30	56.57±14.54
Musk	11.94±0.00	22.46±5.66	17.63±2.87	81.61±13.57	83.06±15.68	81.71±15.73	81.62±15.76
Vowe.	90.15±0.00	80.95±8.06	81.52±8.03	65.28±15.34	64.70±15.71	64.70±15.71	64.70±15.71
Lymp.	55.34±31.95	62.98±26.74	61.65±27.33	67.38±25.37	66.76±25.49	66.71±25.44	66.71±25.44
Glass	26.88±13.60	31.65±13.68	31.18±13.19	42.99±20.17	43.76±20.27	43.79±20.25	43.79±20.24
Wilt	39.47±8.13	40.43±10.08	40.22±10.48	39.29±7.51	39.34±7.22	39.36±7.24	39.36±7.24
Lett.	56.33±0.00	55.79±0.80	55.79±0.75	52.74±3.51	53.08±3.83	53.03±3.79	53.03±3.79
Annt.	44.18±0.00	58.68±9.33	59.36±9.35	51.42±7.41	48.54±6.95	48.54±6.98	48.54±6.98
Wine	95.80±0.00	93.29±2.47	93.50±2.42	87.24±7.58	86.42±9.16	86.34±9.34	86.34±9.34
Stam.	66.81±0.00	65.16±14.80	65.41±14.80	62.12±16.89	62.01±16.94	62.00±16.96	62.00±16.96
Mnist	58.28±0.00	76.04±8.82	76.77±8.68	69.56±4.43	69.49±4.81	69.38±4.88	69.44±4.96
Page.	70.92±0.00	41.65±12.59	42.12±13.48	50.54±14.04	50.19±13.94	50.16±13.94	50.16±13.94
Vert.	35.04±6.00	34.44±12.88	33.73±11.62	31.78±7.28	31.78±7.55	31.78±7.55	31.77±7.54
Card.	60.06±0.00	62.02±8.09	61.54±7.61	66.39±10.35	66.28±10.34	66.27±10.33	66.27±10.33
WPBC	56.47±0.00	55.53±0.72	55.55±0.76	54.28±2.10	54.44±2.08	54.62±2.17	54.45±2.06
Sate.	38.03±0.00	39.75±0.82	39.64±0.76	49.47±3.19	49.39±3.09	49.42±3.07	49.42±3.07
Pima	76.08±0.00	74.13±2.73	74.33±2.75	73.51±3.78	73.51±3.80	73.51±3.79	73.51±3.79
Brea.	99.53±0.00	93.91±8.23	95.01±5.51	98.54±0.87	98.51±0.93	98.51±0.93	98.51±0.93
Iono.	32.83±0.00	33.98±0.74	33.95±0.77	51.07±4.81	51.21±4.82	51.24±4.86	51.51±4.67
Spam.	60.31±0.00	42.00±8.29	42.67±8.78	57.83±1.89	57.95±1.66	57.94±1.64	57.93±1.64
Hear.	85.21±0.00	82.90±2.02	83.49±2.02	79.52±5.45	78.64±5.20	78.65±5.22	78.65±5.22
Arrh.	55.38±0.00	55.34±0.43	55.29±0.47	59.43±4.22	59.65±3.88	59.98±4.11	59.90±4.03
Park.	79.08±0.00	75.59±4.36	75.96±3.43	65.28±8.85	65.37±8.79	65.40±8.78	65.40±8.78

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.34±0.07	0.34±0.06	0.30±0.20	0.29±0.20	0.29±0.20	0.29±0.20
Sati.	1.89±0.00	3.99±1.82	3.75±1.39	65.24±21.56	68.96±19.21	68.77±19.15	68.78±19.14
Shut.	17.14±0.00	16.94±12.71	17.29±12.81	13.19±10.87	12.98±10.52	12.99±10.51	13.00±10.50
WBC	70.28±0.00	51.08±16.83	52.06±15.14	66.64±6.44	66.77±6.43	66.77±6.41	66.77±6.41
Thyr.	16.99±20.81	32.30±23.82	32.90±25.31	24.41±18.80	25.19±19.60	25.20±19.62	25.21±19.63
WDBC	70.66±0.00	66.88±3.17	66.93±3.25	59.80±10.16	59.38±11.21	59.38±11.21	59.60±11.34
Optd.	3.41±0.00	3.23±1.75	3.10±1.55	3.33±1.45	3.29±1.26	3.28±1.25	3.28±1.25
Wave.	2.88±0.00	3.52±0.94	3.45±0.90	3.89±1.41	3.84±1.49	3.81±1.45	3.86±1.50
Musk	1.72±0.00	2.81±1.25	2.19±0.45	41.90±22.85	45.86±22.47	44.64±22.94	44.56±22.88
Vowe.	39.78±0.00	21.51±16.16	22.34±16.59	12.22±14.59	12.00±14.39	12.00±14.40	12.00±14.40
Lymp.	43.92±27.87	45.32±28.11	45.21±28.14	46.21±28.03	46.56±28.52	46.12±28.17	46.12±28.17
Glass	3.37±1.90	3.12±0.77	3.07±0.70	4.22±1.78	4.23±1.75	4.23±1.75	4.23±1.75
Wilt	4.06±0.63	4.17±0.78	4.17±0.88	4.02±0.49	4.01±0.45	4.02±0.45	4.02±0.45
Lett.	7.42±0.00	7.33±0.17	7.32±0.15	7.15±1.20	7.30±1.31	7.30±1.30	7.30±1.30
Annt.	7.43±0.00	13.16±6.01	13.20±5.66	9.12±1.55	8.45±1.40	8.45±1.40	8.45±1.40
Wine	49.35±0.00	41.68±7.30	42.32±7.06	32.86±17.49	32.38±17.65	32.36±17.68	32.36±17.68
Stam.	15.64±0.00	17.00±5.38	17.04±5.48	16.72±7.84	16.61±7.71	16.61±7.71	16.61±7.71
Mnist	22.31±0.00	34.27±10.91	34.53±9.72	28.32±2.17	28.32±2.27	28.30±2.25	28.33±2.30
Page.	35.38±0.00	24.09±10.86	23.80±11.68	28.85±12.48	28.93±12.16	28.91±12.14	28.91±12.14
Vert.	9.08±0.96	9.38±2.17	9.18±1.85	8.65±0.84	8.67±0.89	8.67±0.89	8.67±0.89
Card.	28.82±0.00	33.04±4.22	32.64±3.86	38.38±9.01	38.14±8.87	38.14±8.85	38.14±8.85
WPBC	25.68±0.00	25.09±0.44	25.10±0.47	24.92±1.71	25.07±1.75	25.14±1.71	25.06±1.74
Sate.	24.44±0.00	25.38±0.61	25.30±0.47	42.90±7.91	43.01±8.21	43.13±8.21	43.13±8.21
Pima	61.69±0.00	59.13±2.69	59.33±2.63	57.82±4.08	57.86±4.10	57.86±4.09	57.86±4.09
Brea.	99.11±0.00	93.71±7.46	94.70±5.05	97.66±1.19	97.63±1.26	97.62±1.28	97.62±1.28
Iono.	30.87±0.00	31.86±0.52	31.86±0.52	51.27±4.83	51.24±4.82	51.25±4.83	51.31±4.82
Spam.	44.11±0.00	35.74±3.96	35.98±4.26	42.62±1.19	42.69±1.06	42.67±1.04	42.67±1.04
Hear.	81.29±0.00	78.06±2.43	78.72±2.33	73.32±5.76	72.13±6.07	72.14±6.09	72.15±6.09
Arrh.	56.00±0.00	56.25±0.31	55.97±0.38	60.23±4.11	60.77±3.68	61.03±4.01	60.98±3.96
Park.	93.37±0.00	91.86±1.65	92.07±1.22	86.99±4.25	87.09±4.22	87.11±4.24	87.10±4.24

Table A37: AE(Layers=3, ReLU=yes, Bias=yes, loss=SL1, scoring=SL1)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	66.42±7.07	66.77±6.61	61.19±17.21	60.47±17.28	60.46±17.28	60.46±17.28
Sati.	67.11±0.00	71.08±2.06	70.53±1.97	90.31±5.59	90.05±5.74	90.18±5.82	90.18±5.82
Shut.	86.93±0.00	75.36±36.85	75.88±35.57	76.82±26.15	75.43±26.77	75.42±26.79	75.42±26.79
WBC	98.65±0.00	88.80±15.07	90.48±10.36	97.72±2.26	97.70±1.98	97.69±2.02	97.69±2.02
Thyr.	45.04±0.00	55.07±21.60	52.10±22.64	55.63±22.72	54.82±22.41	54.80±22.40	54.81±22.41
WDBC	97.68±0.00	97.24±0.73	97.27±0.59	96.71±0.79	96.57±0.84	96.57±0.84	96.58±0.84
Optd.	59.10±0.00	55.65±13.60	53.62±14.81	54.64±11.96	54.16±11.61	54.50±11.09	54.79±11.68
Wave.	51.22±0.00	54.12±5.72	53.26±5.16	54.15±13.42	54.08±13.27	54.08±13.28	54.08±13.28
Musk	11.94±0.00	18.29±5.04	16.80±3.91	68.95±11.16	72.26±11.84	72.16±11.44	73.09±12.45
Vowe.	90.15±0.00	84.30±4.81	84.19±5.17	78.61±9.14	78.62±8.96	78.62±8.95	78.62±8.95
Lymp.	66.46±17.95	72.01±17.17	71.31±17.35	75.45±14.99	75.41±15.22	75.41±15.22	75.41±15.22
Glass	20.22±0.00	37.44±22.89	36.35±23.80	37.54±20.48	37.18±19.85	37.17±19.86	37.18±19.87
Wilt	41.08±11.68	41.01±15.60	40.18±15.57	41.16±14.45	41.21±14.22	41.22±14.21	41.22±14.21
Lett.	56.33±0.00	56.56±0.50	56.59±0.58	54.71±4.35	54.57±4.53	54.57±4.53	54.58±4.53
Annt.	44.18±0.00	59.81±13.80	60.78±12.64	54.06±12.43	51.99±11.19	51.85±11.08	51.96±11.21
Wine	95.80±0.00	93.72±2.66	93.86±2.39	91.37±4.85	91.34±5.07	91.35±5.07	91.35±5.07
Stam.	66.81±0.00	71.61±10.23	69.92±10.75	76.61±9.26	76.23±9.32	76.23±9.33	76.23±9.33
Mnist	58.28±0.00	77.55±4.51	76.48±6.46	68.21±2.22	68.12±2.10	68.07±2.23	68.07±2.23
Page.	70.92±0.00	53.12±14.98	53.74±14.37	62.45±14.55	62.13±14.16	62.15±14.17	62.15±14.17
Vert.	31.62±0.00	35.78±12.44	36.37±12.46	32.19±12.87	32.33±12.73	32.32±12.73	32.32±12.73
Card.	60.06±0.00	65.36±7.19	65.69±7.68	63.09±8.09	61.33±7.49	61.34±7.45	61.33±7.45
WPBC	56.47±0.00	56.32±0.64	56.38±0.66	55.32±1.99	55.02±2.22	55.03±2.23	55.03±2.23
Sate.	38.03±0.00	39.22±0.77	39.04±0.74	46.53±3.79	46.88±3.60	46.84±3.55	46.84±3.54
Pima	76.08±0.00	73.84±3.15	73.66±3.21	71.97±4.76	72.02±4.84	72.02±4.84	72.02±4.84
Brea.	99.53±0.00	95.92±5.47	96.50±4.35	98.91±0.67	98.88±0.73	98.88±0.73	98.88±0.73
Iono.	32.83±0.00	33.85±0.48	33.79±0.50	54.09±6.36	53.90±6.58	53.89±6.57	53.89±6.58
Spam.	60.31±0.00	43.24±10.50	40.50±9.74	58.95±0.75	58.78±1.18	58.79±1.13	58.79±1.13
Hear.	85.21±0.00	82.88±2.81	82.99±2.85	80.83±5.85	80.99±5.90	81.01±5.89	81.01±5.89
Arrh.	55.38±0.00	55.48±0.27	55.51±0.19	59.52±5.44	59.71±4.37	60.09±4.52	60.16±4.49
Park.	79.08±0.00	75.60±5.47	75.89±5.48	65.59±11.05	65.73±11.28	65.75±11.29	65.75±11.30

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.50±0.43	0.87±1.53	0.92±1.60	0.91±1.61	0.91±1.61	0.91±1.61
Sati.	1.89±0.00	2.79±0.55	2.58±0.43	51.54±22.77	50.49±21.93	51.38±22.36	51.39±22.37
Shut.	17.14±0.00	25.01±21.07	23.70±17.64	20.96±19.10	20.82±19.64	20.83±19.67	20.83±19.67
WBC	70.28±0.00	56.81±16.36	56.85±15.26	68.47±2.02	68.15±2.67	68.15±2.67	68.15±2.67
Thyr.	10.10±0.00	12.59±8.29	11.69±7.88	13.32±7.93	13.28±8.37	13.28±8.37	13.28±8.37
WDBC	70.66±0.00	68.65±3.98	68.17±3.44	64.33±6.33	63.28±6.72	63.34±6.67	63.34±6.68
Optd.	3.41±0.00	3.30±1.17	3.10±0.95	3.26±1.24	3.16±0.98	3.17±0.97	3.24±1.15
Wave.	2.88±0.00	3.18±0.52	3.10±0.45	3.51±1.22	3.49±1.17	3.49±1.17	3.49±1.17
Musk	1.72±0.00	3.28±1.10	2.40±0.65	23.41±9.97	25.56±13.98	25.02±12.10	27.44±15.51
Vowe.	39.78±0.00	22.70±11.86	22.73±12.17	18.30±14.45	18.14±14.37	18.15±14.38	18.16±14.38
Lymp.	50.80±23.94	46.72±24.03	47.59±23.51	56.63±18.25	56.76±18.50	56.76±18.50	56.76±18.50
Glass	2.45±0.00	4.55±2.75	4.39±2.80	4.37±1.89	4.32±1.80	4.32±1.81	4.32±1.81
Wilt	4.26±0.89	4.69±2.05	4.60±1.96	4.57±1.82	4.56±1.77	4.56±1.77	4.56±1.77
Lett.	7.42±0.00	7.53±0.11	7.54±0.17	7.42±1.16	7.40±1.22	7.40±1.23	7.40±1.23
Annt.	7.43±0.00	16.06±8.41	16.09±8.78	10.47±3.53	9.65±3.02	9.61±3.00	9.65±3.03
Wine	49.35±0.00	43.19±8.41	43.56±7.68	39.59±12.74	39.64±13.11	39.73±13.18	39.73±13.18
Stam.	15.64±0.00	20.31±6.93	19.40±7.14	23.42±7.47	23.24±7.75	23.25±7.76	23.25±7.76
Mnist	22.31±0.00	34.08±6.75	33.61±7.99	27.70±1.59	27.63±1.64	27.56±1.66	27.57±1.66
Page.	35.38±0.00	29.10±12.15	29.63±11.17	35.93±11.38	36.69±11.81	36.70±11.80	36.70±11.80
Vert.	8.56±0.00	9.84±3.43	10.02±3.82	9.20±2.80	9.23±2.84	9.22±2.84	9.22±2.84
Card.	28.82±0.00	34.56±6.05	35.09±6.10	34.12±5.23	33.01±3.48	33.01±3.47	33.01±3.47
WPBC	25.68±0.00	25.62±0.44	25.67±0.41	25.33±1.62	25.19±1.78	25.18±1.79	25.18±1.79
Sate.	24.44±0.00	25.03±0.37	24.93±0.34	38.57±7.52	38.82±7.10	38.69±7.07	38.69±7.06
Pima	61.69±0.00	59.07±2.63	59.01±2.65	57.18±4.10	57.20±4.06	57.20±4.06	57.20±4.06
Brea.	99.11±0.00	95.57±5.09	96.00±4.25	98.37±0.66	98.34±0.72	98.34±0.72	98.34±0.72
Iono.	30.87±0.00	31.66±0.33	31.58±0.33	50.37±5.46	50.58±5.96	50.55±5.95	50.57±5.95
Spam.	44.11±0.00	36.21±5.19	34.85±4.38	43.29±0.53	43.20±0.84	43.21±0.83	43.21±0.83
Hear.	81.29±0.00	78.49±3.88	78.56±3.96	76.00±7.46	76.30±7.47	76.35±7.45	76.35±7.45
Arrh.	56.00±0.00	56.12±0.23	56.11±0.13	59.77±4.87	60.00±4.17	60.23±4.11	60.30±4.13
Park.	93.37±0.00	91.93±2.32	92.01±2.27	86.76±5.31	86.81±5.43	86.82±5.45	86.82±5.45

Table A38: AE(Layers=4, ReLU=yes, Bias=yes, loss=SL1, scoring=SL1)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	66.94±6.47	66.10±7.34	57.85±22.06	57.39±22.27	57.44±22.22	57.44±22.22
Sati.	67.11±0.00	69.75±2.40	70.18±2.02	86.89±6.65	87.54±6.62	87.55±6.67	87.54±6.66
Shut.	86.93±0.00	80.65±10.57	78.63±14.55	75.00±19.82	75.45±19.54	75.43±19.54	75.43±19.54
WBC	98.65±0.00	92.92±5.26	92.36±6.36	98.41±0.25	98.39±0.28	98.39±0.29	98.39±0.29
Thyr.	45.04±0.00	48.62±35.54	48.12±35.96	53.42±28.87	53.14±29.35	53.11±29.36	53.11±29.36
WDBC	97.68±0.00	97.35±0.38	97.34±0.32	96.63±0.94	96.44±1.05	96.43±1.05	96.43±1.05
Optd.	59.10±0.00	63.84±15.71	62.54±17.23	62.75±8.38	62.67±8.25	62.69±8.17	62.69±8.18
Wave.	51.22±0.00	54.34±4.44	53.86±4.58	59.28±15.06	59.23±15.18	59.22±15.19	59.22±15.19
Musk	11.94±0.00	17.18±3.63	15.72±3.53	65.33±19.36	63.79±18.35	63.84±18.50	63.89±18.46
Vowe.	90.15±0.00	83.83±10.76	84.16±10.51	73.64±17.51	73.66±17.76	73.64±17.77	73.64±17.77
Lymp.	55.34±31.95	62.98±26.74	61.65±27.33	67.38±25.37	66.76±25.49	66.71±25.44	66.71±25.44
Glass	20.22±0.00	29.39±17.74	29.10±16.97	32.41±16.17	31.76±16.16	31.75±16.16	31.75±16.16
Wilt	39.87±14.27	41.10±14.94	41.48±14.68	37.65±10.93	37.45±10.77	37.46±10.77	37.45±10.78
Lett.	56.33±0.00	56.15±0.84	56.10±0.81	54.12±2.99	54.16±2.53	54.16±2.53	54.16±2.53
Annt.	44.18±0.00	55.89±11.15	55.42±13.24	48.10±9.69	48.90±8.43	48.98±8.46	48.98±8.46
Wine	95.80±0.00	94.63±1.39	94.50±1.40	91.16±4.22	91.06±4.43	91.05±4.46	91.06±4.46
Stam.	66.81±0.00	60.77±12.51	61.01±12.72	57.69±19.75	58.60±19.00	58.61±18.99	58.61±18.99
Mnist	58.28±0.00	80.45±8.75	79.45±11.04	68.14±3.99	68.90±4.35	68.40±4.06	68.40±4.06
Page.	70.92±0.00	58.90±18.05	58.82±16.78	70.11±10.76	67.83±12.08	67.86±12.07	67.86±12.07
Vert.	31.62±0.00	35.22±9.39	34.61±9.62	33.80±5.95	33.84±5.66	33.84±5.67	33.84±5.67
Card.	60.06±0.00	62.63±7.84	62.80±8.52	60.80±9.15	61.16±9.15	61.16±9.14	61.16±9.14
WPBC	56.47±0.00	56.10±0.62	56.20±0.70	55.34±2.34	55.43±2.38	55.36±2.48	55.36±2.48
Sate.	38.03±0.00	38.70±0.91	38.86±0.77	46.20±3.37	44.73±4.37	44.73±4.38	44.73±4.38
Pima	76.08±0.00	76.13±4.15	76.00±4.15	76.37±3.10	76.34±3.01	76.35±3.01	76.35±3.01
Brea.	99.53±0.00	98.81±0.38	98.73±0.49	99.07±0.29	99.05±0.32	99.05±0.32	99.05±0.32
Iono.	32.83±0.00	33.98±1.01	33.84±0.91	47.24±3.79	47.51±4.18	47.70±3.98	47.70±3.99
Spam.	60.31±0.00	44.44±8.72	44.32±5.75	58.59±1.64	58.51±1.86	58.42±1.75	58.42±1.75
Hear.	85.21±0.00	82.53±4.79	82.40±4.87	80.23±3.79	80.30±3.54	80.31±3.54	80.31±3.54
Arrh.	55.38±0.00	55.41±0.27	55.45±0.18	59.19±2.46	58.99±2.55	59.31±2.59	59.21±2.76
Park.	79.08±0.00	77.24±3.57	77.00±4.17	71.43±9.52	70.73±9.90	70.77±9.89	70.77±9.89

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.37±0.09	0.36±0.09	0.45±0.41	0.44±0.41	0.44±0.41	0.44±0.41
Sati.	1.89±0.00	2.57±1.05	2.75±1.08	39.57±24.22	41.51±23.63	41.61±23.78	41.57±23.72
Shut.	17.14±0.00	14.93±6.50	14.51±6.81	13.92±9.48	13.88±9.50	13.88±9.50	13.88±9.49
WBC	70.28±0.00	60.31±6.56	59.72±6.62	68.50±1.34	68.40±1.74	68.43±1.77	68.43±1.77
Thyr.	10.10±0.00	21.58±26.11	20.16±24.41	16.88±15.52	17.73±17.04	17.73±17.05	17.72±17.05
WDBC	70.66±0.00	67.83±2.28	67.71±2.00	63.61±8.14	63.05±8.08	62.88±8.06	62.80±8.20
Optd.	3.41±0.00	4.73±2.90	4.47±2.41	3.80±0.94	3.79±0.94	3.79±0.93	3.79±0.93
Wave.	2.88±0.00	3.18±0.36	3.14±0.37	4.17±1.48	4.17±1.45	4.17±1.46	4.17±1.46
Musk	1.72±0.00	2.26±0.50	1.97±0.24	24.24±18.60	21.35±15.04	21.55±15.39	21.62±15.34
Vowe.	39.78±0.00	31.08±20.16	31.73±18.91	23.19±25.02	23.16±25.04	23.16±25.05	23.16±25.05
Lymp.	43.92±27.87	45.32±28.11	45.21±28.14	46.21±28.03	46.56±28.52	46.12±28.17	46.12±28.17
Glass	2.45±0.00	3.34±1.53	3.31±1.43	3.34±1.05	3.34±1.12	3.34±1.12	3.34±1.12
Wilt	4.41±1.61	4.54±1.75	4.56±1.77	4.03±0.92	4.02±0.95	4.02±0.95	4.02±0.95
Lett.	7.42±0.00	7.42±0.22	7.40±0.22	7.15±0.72	7.14±0.71	7.14±0.71	7.14±0.71
Annt.	7.43±0.00	11.24±4.24	11.90±5.61	8.67±1.99	8.71±1.67	8.72±1.67	8.72±1.67
Wine	49.35±0.00	45.28±4.34	45.58±5.75	36.26±11.56	36.10±11.69	36.08±11.72	36.11±11.71
Stam.	15.64±0.00	15.88±3.87	15.89±4.04	16.09±6.45	15.95±6.59	15.96±6.60	15.96±6.60
Mnist	22.31±0.00	40.27±7.86	39.84±8.72	27.54±2.45	28.08±2.74	27.64±2.48	27.64±2.48
Page.	35.38±0.00	38.45±19.03	37.20±16.18	39.24±10.77	38.06±10.52	38.07±10.53	38.07±10.53
Vert.	8.56±0.00	9.26±1.44	9.15±1.29	8.86±0.64	8.86±0.61	8.86±0.61	8.86±0.61
Card.	28.82±0.00	32.23±6.25	32.49±6.89	32.65±6.70	32.92±6.65	32.93±6.64	32.93±6.64
WPBC	25.68±0.00	25.53±0.52	25.57±0.55	25.46±1.34	25.51±1.35	25.44±1.42	25.44±1.42
Sate.	24.44±0.00	24.79±0.49	24.86±0.42	37.93±6.39	35.93±7.42	35.93±7.43	35.94±7.43
Pima	61.69±0.00	60.94±3.28	60.90±3.27	60.78±3.94	60.75±3.85	60.76±3.85	60.76±3.85
Brea.	99.11±0.00	98.18±0.48	98.10±0.56	98.49±0.34	98.47±0.37	98.47±0.37	98.47±0.37
Iono.	30.87±0.00	31.73±0.35	31.65±0.31	46.99±3.31	47.47±4.03	47.67±3.84	47.66±3.83
Spam.	44.11±0.00	36.77±4.29	36.50±2.75	43.00±1.07	42.96±1.25	42.90±1.18	42.90±1.18
Hear.	81.29±0.00	77.96±5.43	77.75±5.26	74.08±4.92	74.14±4.64	74.07±4.59	74.07±4.59
Arrh.	56.00±0.00	56.11±0.24	56.10±0.18	60.15±2.14	59.98±2.25	60.22±2.38	60.12±2.53
Park.	93.37±0.00	92.63±1.32	92.50±1.57	89.90±4.15	89.54±4.36	89.55±4.36	89.55±4.36

Table A39: AE(Layers=5, ReLU=yes, Bias=yes, loss=SL1, scoring=SL1)'s results of AUROC and AUPRC (mean±SD, %)

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	64.36±5.31	65.14±4.60	55.95±15.24	55.90±15.11	55.89±15.13	55.89±15.13
Sati.	67.11±0.00	70.52±1.43	69.88±1.35	87.14±7.12	86.62±8.07	86.41±7.95	86.60±8.05
Shut.	86.93±0.00	84.29±17.71	82.04±20.06	82.63±15.35	82.84±14.63	82.82±14.64	82.82±14.64
WBC	98.65±0.00	92.02±7.62	89.97±10.56	97.45±2.97	97.41±2.99	97.41±2.99	97.41±2.99
Thyr.	45.04±0.00	83.19±9.30	82.39±10.62	76.30±15.66	76.12±16.65	76.13±16.65	76.13±16.65
WDBC	97.68±0.00	97.53±0.20	97.43±0.27	96.57±0.95	96.57±0.91	96.58±0.90	96.58±0.90
Optd.	59.10±0.00	52.73±16.44	57.39±18.85	58.45±7.63	58.42±7.09	58.45±7.12	58.45±7.12
Wave.	51.22±0.00	53.43±4.10	53.23±4.79	48.83±11.34	48.67±11.48	48.67±11.48	48.67±11.49
Musk	11.94±0.00	20.61±5.02	18.05±2.91	54.58±17.53	56.80±17.66	57.09±17.93	57.07±17.94
Vowe.	90.15±0.00	87.75±5.06	87.40±5.28	73.89±12.13	74.12±12.48	74.11±12.48	74.11±12.48
Lymp.	55.34±31.95	62.98±26.74	61.65±27.33	67.38±25.37	66.76±25.49	66.71±25.44	66.71±25.44
Glass	20.22±0.00	32.48±21.19	31.38±22.78	39.40±27.39	38.53±27.38	38.53±27.38	38.53±27.38
Wilt	32.45±0.00	35.51±9.59	34.85±9.64	36.23±10.12	36.40±10.20	36.40±10.20	36.40±10.20
Lett.	56.33±0.00	55.94±0.47	56.00±0.51	54.47±3.06	54.41±3.03	54.50±2.85	54.50±2.85
Annt.	44.18±0.00	61.56±11.57	59.32±11.84	52.03±12.08	49.66±11.14	49.65±11.12	49.65±11.12
Wine	95.80±0.00	94.82±1.85	94.84±1.46	92.02±3.58	92.13±3.55	92.12±3.55	92.12±3.55
Stam.	66.81±0.00	64.17±11.21	63.89±11.06	59.78±19.57	59.83±19.52	59.84±19.51	59.84±19.51
Mnist	58.28±0.00	73.06±11.73	74.52±10.82	68.07±4.55	68.11±4.87	68.19±4.90	68.19±4.90
Page.	70.92±0.00	50.58±19.18	52.75±17.68	69.94±10.35	70.44±10.06	70.40±10.09	70.40±10.09
Vert.	31.62±0.00	35.30±8.55	35.45±9.04	29.97±6.76	30.15±7.24	30.14±7.24	30.14±7.24
Card.	60.06±0.00	63.80±6.20	63.59±5.52	63.69±9.77	64.05±10.29	64.03±10.28	64.03±10.28
WPBC	56.47±0.00	56.21±0.89	56.20±0.75	55.78±1.49	55.87±1.54	55.86±1.53	55.87±1.53
Sate.	38.03±0.00	39.03±0.47	38.82±0.45	45.88±3.83	45.74±4.14	45.72±4.12	45.72±4.12
Pima	76.08±0.00	75.22±1.06	74.97±1.19	73.98±2.10	74.03±2.07	74.03±2.07	74.03±2.07
Brea.	99.53±0.00	98.69±0.92	98.40±1.50	99.00±0.56	99.01±0.53	99.01±0.53	99.01±0.53
Iono.	32.83±0.00	34.08±0.91	34.03±0.84	50.67±6.87	50.99±6.72	51.38±7.15	51.53±7.36
Spam.	60.31±0.00	44.13±8.96	43.13±9.11	59.36±2.08	59.13±2.03	59.14±2.05	59.12±2.04
Hear.	85.21±0.00	81.53±4.69	81.71±3.97	78.69±5.03	78.85±4.76	78.86±4.76	78.86±4.76
Arrh.	55.38±0.00	55.54±0.12	55.51±0.13	60.27±2.46	60.25±2.07	60.45±2.26	60.49±2.27
Park.	79.08±0.00	77.08±2.28	76.86±2.12	69.18±6.86	68.65±6.76	68.65±6.76	68.64±6.76

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.41±0.26	0.36±0.12	0.28±0.15	0.27±0.15	0.27±0.15	0.27±0.15
Sati.	1.89±0.00	2.53±0.39	2.37±0.33	38.86±26.31	38.67±26.99	37.70±27.02	38.50±27.00
Shut.	17.14±0.00	21.34±11.95	18.52±8.66	19.04±12.87	18.19±12.00	18.18±11.98	18.18±11.98
WBC	70.28±0.00	59.28±11.61	58.37±12.62	67.82±3.03	67.19±4.25	67.19±4.25	67.19±4.25
Thyr.	10.10±0.00	30.69±15.10	30.88±16.85	27.43±17.73	28.11±18.10	28.12±18.12	28.12±18.12
WDBC	70.66±0.00	68.36±1.89	68.10±1.86	64.29±3.08	64.36±3.40	64.40±3.35	64.40±3.35
Optd.	3.41±0.00	3.25±1.58	4.22±3.25	3.40±0.78	3.37±0.75	3.38±0.75	3.38±0.75
Wave.	2.88±0.00	3.11±0.38	3.10±0.45	2.99±0.78	2.98±0.79	2.98±0.79	2.98±0.79
Musk	1.72±0.00	2.84±1.20	2.08±0.35	14.48±16.60	14.94±15.99	14.87±16.06	14.88±16.05
Vowe.	39.78±0.00	29.12±13.38	29.60±12.67	15.65±16.31	15.84±16.65	15.83±16.64	15.84±16.64
Lymp.	43.92±27.87	45.32±28.11	45.21±28.14	46.21±28.03	46.56±28.52	46.12±28.17	46.12±28.17
Glass	2.45±0.00	3.52±1.70	3.61±1.97	4.51±2.74	4.41±2.63	4.41±2.63	4.41±2.63
Wilt	3.57±0.00	3.85±0.70	3.82±0.76	3.92±0.85	3.93±0.85	3.93±0.85	3.93±0.85
Lett.	7.42±0.00	7.41±0.10	7.43±0.12	7.30±0.76	7.27±0.74	7.27±0.74	7.27±0.74
Annt.	7.43±0.00	14.84±6.88	13.81±7.06	9.55±2.78	8.92±2.35	8.92±2.34	8.92±2.34
Wine	49.35±0.00	47.27±5.74	46.64±4.61	39.30±10.44	39.72±10.50	39.63±10.48	39.63±10.48
Stam.	15.64±0.00	18.33±7.71	18.14±7.00	17.92±9.54	17.91±9.46	17.92±9.46	17.92±9.46
Mnist	22.31±0.00	33.96±10.47	35.13±10.46	27.46±2.52	27.56±2.71	27.60±2.73	27.60±2.73
Page.	35.38±0.00	26.70±15.63	27.64±15.42	38.22±13.68	39.04±13.98	39.02±14.00	39.02±14.00
Vert.	8.56±0.00	9.07±1.14	9.11±1.22	8.40±0.68	8.43±0.74	8.43±0.74	8.43±0.74
Card.	28.82±0.00	32.32±4.37	32.15±3.87	35.83±7.53	35.89±8.01	35.87±7.99	35.87±7.99
WPBC	25.68±0.00	25.48±0.69	25.47±0.60	25.30±0.89	25.34±0.87	25.34±0.87	25.34±0.87
Sate.	24.44±0.00	24.90±0.24	24.79±0.22	35.56±8.02	35.75±8.31	35.68±8.34	35.69±8.33
Pima	61.69±0.00	60.68±0.85	60.41±1.02	59.46±2.13	59.39±2.24	59.39±2.23	59.39±2.23
Brea.	99.11±0.00	98.09±0.98	97.81±1.51	98.45±0.52	98.46±0.50	98.45±0.50	98.45±0.50
Iono.	30.87±0.00	31.63±0.39	31.62±0.32	47.52±3.82	47.62±3.85	47.80±4.12	48.07±4.70
Spam.	44.11±0.00	36.57±3.99	36.04±3.99	43.50±1.32	43.37±1.27	43.37±1.29	43.35±1.28
Hear.	81.29±0.00	76.11±5.58	76.39±4.79	72.39±6.40	72.53±6.17	72.57±6.13	72.57±6.13
Arrh.	56.00±0.00	56.20±0.15	56.13±0.08	61.24±2.30	61.17±2.02	61.40±2.33	61.33±2.31
Park.	93.37±0.00	92.61±0.84	92.54±0.81	88.98±3.39	88.73±3.31	88.73±3.31	88.72±3.31

Table A40: AE (Layers=3, ReLU=Yes, Bias=No, loss=L2, scoring=L1): AUROC and AUPRC (mean±SD, %).

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	68.40±0.00	68.45±0.37	68.34±0.30	55.18±26.65	55.56±27.29	55.57±27.31	55.57±27.30
Sati.	43.38±0.00	43.14±0.45	43.21±0.37	99.35±0.13	99.39±0.13	99.39±0.13	99.39±0.13
Shut.	85.37±0.00	85.31±0.55	85.35±0.53	87.42±4.47	87.36±4.91	87.36±4.91	87.36±4.91
WBC	98.83±0.00	98.83±0.01	98.83±0.01	98.80±0.11	98.79±0.13	98.79±0.13	98.79±0.13
Thyr.	27.85±0.00	27.91±0.54	27.88±0.53	32.10±5.57	32.85±5.84	32.85±5.84	32.85±5.84
WDBC	98.15±0.00	98.14±0.02	98.13±0.01	89.99±1.51	89.33±1.34	89.47±1.43	89.46±1.43
Optd.	61.43±0.00	61.37±0.49	61.49±0.43	52.87±2.49	52.01±1.86	52.03±1.89	52.04±1.89
Wave.	45.64±0.00	45.84±0.59	45.83±0.67	60.48±9.65	61.37±7.94	61.43±7.83	61.43±7.83
Musk	0.17±0.00	0.19±0.07	0.18±0.03	99.96±0.02	99.97±0.02	99.97±0.02	99.97±0.02
Vowe.	87.84±0.00	87.76±0.65	87.81±0.52	76.45±11.50	76.87±12.00	76.87±11.99	76.87±11.99
Lymp.	73.77±0.00	73.77±0.00	73.77±0.00	73.77±0.00	73.77±0.00	73.77±0.00	73.77±0.00
Glass	19.95±0.00	19.95±0.62	19.96±0.58	22.03±7.68	23.65±10.99	23.66±10.97	23.66±10.96
Wilt	33.26±0.00	33.24±0.10	33.26±0.09	33.14±0.26	33.13±0.28	33.13±0.28	33.13±0.28
Lett.	57.03±0.00	57.00±0.11	56.99±0.15	50.78±2.38	50.91±2.56	50.92±2.56	50.92±2.55
Annt.	38.60±0.00	38.65±0.28	38.72±0.39	58.92±6.02	57.72±5.47	57.78±5.45	57.78±5.45
Wine	96.55±0.00	96.52±0.10	96.57±0.13	81.76±19.44	82.52±16.25	82.48±16.29	82.48±16.29
Stam.	63.43±0.00	63.43±1.75	63.43±1.57	61.25±6.62	60.69±7.87	60.68±7.87	60.68±7.87
Mnist	39.78±0.00	39.93±0.37	39.86±0.35	80.57±0.94	81.08±0.56	81.10±0.51	81.10±0.50
Page.	67.65±0.00	67.62±0.11	67.63±0.04	69.42±3.42	69.84±4.28	69.84±4.29	69.84±4.29
Vert.	31.89±0.00	31.88±0.19	31.90±0.16	31.42±0.87	31.35±1.08	31.35±1.08	31.35±1.08
Card.	53.69±0.00	53.56±0.39	53.61±0.21	69.29±8.05	71.30±8.13	71.35±8.14	71.35±8.14
WPBC	56.87±0.00	56.92±0.05	56.92±0.04	51.56±1.04	51.63±1.00	51.59±1.00	51.66±1.01
Sate.	32.22±0.00	32.15±0.14	32.17±0.11	57.73±1.79	58.21±1.14	58.27±1.09	58.27±1.09
Pima	75.42±0.00	75.40±0.10	75.41±0.11	75.32±2.60	75.43±2.32	75.43±2.32	75.43±2.32
Brea.	99.52±0.00	99.52±0.00	99.52±0.00	99.46±0.17	99.42±0.26	99.42±0.26	99.42±0.26
Iono.	25.51±0.00	25.44±0.23	25.46±0.15	74.52±0.79	75.42±0.73	75.43±0.73	75.44±0.72
Spam.	68.33±0.00	68.29±0.15	68.30±0.13	60.99±0.59	60.76±0.47	60.76±0.48	60.77±0.47
Hear.	86.03±0.00	86.00±0.14	86.02±0.17	79.61±9.39	78.07±10.37	78.07±10.39	78.07±10.39
Arrh.	52.08±0.00	52.07±0.17	52.06±0.11	74.18±0.36	73.89±0.12	73.82±0.34	73.84±0.38
Park.	83.86±0.00	83.86±0.26	83.82±0.28	52.66±8.24	51.40±10.03	51.48±10.10	51.48±10.11

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.35±0.00	0.34±0.01	0.34±0.01	0.43±0.47	0.90±1.86	0.90±1.86	0.90±1.86
Sati.	1.00±0.00	1.00±0.01	1.00±0.01	95.28±0.17	95.31±0.14	95.31±0.14	95.31±0.14
Shut.	16.10±0.00	15.87±0.47	16.03±0.23	16.18±5.86	16.60±7.59	16.60±7.59	16.60±7.59
WBC	71.51±0.00	71.58±0.19	71.55±0.12	70.84±2.54	71.01±2.02	71.01±2.00	71.01±2.00
Thyr.	2.64±0.00	2.69±0.11	2.69±0.11	3.94±1.43	4.13±1.57	4.13±1.57	4.13±1.57
WDBC	76.51±0.00	76.48±0.04	76.47±0.03	44.35±4.85	42.17±4.15	42.62±4.36	42.61±4.37
Optd.	3.92±0.00	3.91±0.08	3.93±0.06	2.77±0.17	2.72±0.12	2.72±0.12	2.72±0.12
Wave.	2.57±0.00	2.59±0.04	2.59±0.05	4.09±0.92	4.11±0.86	4.12±0.86	4.12±0.86
Musk	1.60±0.00	1.60±0.00	1.60±0.00	98.60±0.57	99.15±0.49	99.17±0.52	99.18±0.52
Vowe.	39.26±0.00	37.84±1.68	37.98±1.58	18.86±12.33	20.63±13.94	20.62±14.00	20.58±13.98
Lymp.	68.15±0.00	68.15±0.00	68.15±0.00	68.15±0.00	68.15±0.00	68.15±0.00	68.15±0.00
Glass	2.44±0.00	2.44±0.01	2.44±0.01	2.54±0.25	2.68±0.57	2.68±0.57	2.68±0.57
Wilt	3.60±0.00	3.60±0.01	3.60±0.00	3.60±0.01	3.60±0.01	3.60±0.01	3.60±0.01
Lett.	7.41±0.00	7.41±0.02	7.41±0.04	6.30±0.29	6.36±0.33	6.36±0.33	6.36±0.33
Annt.	5.68±0.00	5.69±0.03	5.70±0.05	10.80±2.57	10.23±2.33	10.26±2.33	10.26±2.33
Wine	52.47±0.00	52.34±0.81	52.66±0.94	31.72±18.00	32.79±18.02	32.77±18.04	32.77±18.04
Stam.	14.35±0.00	14.37±0.89	14.36±0.77	13.63±2.12	13.61±2.23	13.60±2.23	13.60±2.23
Mnist	10.56±0.00	10.61±0.16	10.60±0.10	32.14±1.01	32.32±0.64	32.30±0.60	32.31±0.60
Page.	31.00±0.00	30.99±0.24	31.00±0.22	34.24±7.89	34.82±9.40	34.82±9.40	34.82±9.40
Vert.	8.57±0.00	8.57±0.02	8.57±0.02	8.52±0.09	8.52±0.10	8.52±0.10	8.52±0.10
Card.	23.39±0.00	23.35±0.21	23.37±0.12	43.58±8.00	45.33±7.16	45.36±7.15	45.36±7.15
WPBC	26.17±0.00	26.20±0.06	26.22±0.06	23.19±0.95	23.28±0.95	23.27±0.95	23.29±0.95
Sate.	22.86±0.00	22.84±0.04	22.84±0.03	58.57±1.02	58.85±0.67	58.88±0.65	58.88±0.65
Pima	62.14±0.00	62.12±0.12	62.13±0.12	61.40±2.60	61.34±2.62	61.35±2.62	61.35±2.62
Brea.	99.06±0.00	99.06±0.01	99.07±0.01	98.96±0.26	98.92±0.37	98.92±0.37	98.92±0.37
Iono.	25.83±0.00	25.81±0.07	25.83±0.05	67.25±0.81	67.52±0.91	67.52±0.91	67.53±0.91
Spam.	52.54±0.00	52.47±0.18	52.47±0.15	45.14±0.65	45.08±0.53	45.09±0.53	45.09±0.53
Hear.	84.10±0.00	84.03±0.18	84.05±0.21	74.52±9.79	72.58±11.02	72.57±11.04	72.56±11.04
Arrh.	53.32±0.00	53.28±0.22	53.33±0.11	74.39±0.29	74.15±0.15	74.02±0.45	74.05±0.49
Park.	94.84±0.00	94.85±0.07	94.83±0.08	80.13±5.13	79.32±6.36	79.36±6.38	79.35±6.39

Table A41: AE (Layers=3, ReLU=No, Bias=Yes, loss=L2, scoring=L1): AUROC and AUPRC (mean±SD, %).

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	68.40±0.00	67.80±1.56	68.10±0.88	55.61±15.87	54.19±14.62	54.16±14.68	54.16±14.68
Sati.	43.38±0.00	51.21±4.38	49.33±2.98	99.14±0.22	99.19±0.19	99.19±0.19	99.19±0.19
Shut.	85.37±0.00	86.47±2.51	86.27±2.58	88.16±3.12	88.89±3.52	88.89±3.50	88.89±3.50
WBC	98.83±0.00	96.54±5.90	95.25±9.72	98.64±0.21	98.61±0.25	98.60±0.25	98.60±0.25
Thyr.	27.85±0.00	43.84±33.95	43.90±33.71	63.90±24.10	63.60±25.43	63.62±25.39	63.63±25.39
WDBC	98.15±0.00	97.82±0.45	97.88±0.31	90.50±2.44	89.85±2.48	89.83±2.48	89.83±2.48
Optd.	61.43±0.00	53.47±20.29	50.54±19.52	47.34±3.41	50.04±1.54	50.33±1.98	50.30±1.97
Wave.	45.64±0.00	45.36±2.30	45.32±2.09	59.05±6.64	59.08±6.20	59.23±6.38	59.23±6.38
Musk	0.17±0.00	3.25±3.30	1.35±1.07	99.93±0.05	99.97±0.03	99.97±0.03	99.96±0.03
Vowe.	87.84±0.00	86.61±2.58	87.11±2.25	71.27±10.97	71.64±11.68	71.68±11.74	71.68±11.74
Lymp.	70.41±22.62	69.82±23.13	70.36±22.79	71.53±22.06	71.19±22.30	71.19±22.30	71.19±22.30
Glass	19.95±0.00	41.84±17.65	39.20±18.40	46.73±17.19	45.63±18.00	45.59±17.98	45.59±17.99
Wilt	33.16±4.76	40.22±8.66	39.99±9.25	37.18±8.99	37.66±8.69	37.61±8.74	37.62±8.74
Lett.	57.03±0.00	57.02±0.30	56.98±0.25	49.78±1.51	49.95±2.00	49.94±2.05	49.94±2.05
Annt.	38.60±0.00	54.17±12.90	53.04±12.16	56.59±7.63	56.17±4.93	56.26±4.86	56.26±4.86
Wine	96.55±0.00	96.15±0.37	96.24±0.35	86.12±9.99	83.76±12.12	83.77±12.17	83.77±12.17
Stam.	63.43±0.00	65.40±6.20	64.71±6.44	69.61±11.48	69.87±11.92	69.92±11.80	69.93±11.81
Mnist	39.78±0.00	61.12±14.65	57.24±14.63	85.51±0.89	85.45±0.73	85.41±0.51	85.45±0.50
Page.	67.65±0.00	59.64±20.29	57.71±17.88	72.07±16.33	71.68±16.19	71.68±16.22	71.68±16.21
Vert.	31.89±0.00	47.46±12.99	46.43±11.79	39.49±11.09	40.57±10.18	40.57±10.16	40.57±10.17
Card.	53.69±0.00	59.91±6.30	59.19±7.00	75.20±9.01	75.67±5.83	75.70±5.72	75.70±5.73
WPBC	56.87±0.00	56.86±0.43	56.72±0.63	49.67±0.75	49.35±0.81	49.38±0.85	49.40±0.84
Sate.	32.22±0.00	33.47±0.92	33.10±0.67	64.58±2.53	63.83±1.67	63.86±1.73	63.86±1.74
Pima	75.42±0.00	74.25±3.27	74.05±3.29	74.71±2.16	74.66±2.30	74.66±2.30	74.66±2.30
Brea.	99.52±0.00	98.94±1.43	98.66±2.24	96.97±3.89	97.33±2.75	97.31±2.75	97.31±2.75
Iono.	25.51±0.00	26.67±0.52	26.34±0.51	75.71±1.25	76.13±0.64	76.09±0.65	76.09±0.64
Spam.	68.33±0.00	58.38±9.26	55.39±7.71	56.51±2.26	56.25±1.00	56.37±1.08	56.37±1.08
Hear.	86.03±0.00	84.60±3.44	85.14±2.58	73.00±8.61	72.70±9.20	72.67±9.21	72.67±9.20
Arrh.	52.08±0.00	52.15±0.47	52.10±0.19	73.94±0.20	74.02±0.13	73.97±0.16	74.00±0.18
Park.	83.86±0.00	80.62±2.74	81.76±1.72	39.87±4.84	39.60±4.67	39.64±4.68	39.65±4.68

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.35±0.00	0.34±0.03	0.34±0.02	0.26±0.15	0.27±0.15	0.27±0.15	0.27±0.15
Sati.	1.00±0.00	1.15±0.10	1.11±0.06	94.57±0.49	94.70±0.38	94.71±0.39	94.70±0.39
Shut.	16.10±0.00	14.92±2.30	15.30±2.07	14.64±4.09	14.06±3.63	14.14±3.79	14.14±3.79
WBC	71.51±0.00	66.98±9.13	66.33±9.86	69.81±3.55	69.66±3.91	69.63±3.90	69.63±3.90
Thyr.	2.64±0.00	17.06±22.69	16.94±22.29	18.22±18.36	18.55±19.12	18.54±19.12	18.54±19.12
WDBC	76.51±0.00	75.61±2.69	75.83±1.75	51.96±10.78	49.35±12.62	49.34±12.61	49.34±12.61
Optd.	3.92±0.00	3.55±1.89	3.24±1.69	2.46±0.17	2.59±0.08	2.61±0.11	2.61±0.11
Wave.	2.57±0.00	2.56±0.14	2.56±0.12	3.94±0.76	3.98±0.70	3.98±0.69	3.98±0.69
Musk	1.60±0.00	1.62±0.03	1.61±0.01	97.89±1.59	99.08±0.89	98.99±0.89	98.97±0.93
Vowe.	39.26±0.00	31.29±9.90	32.22±8.67	13.43±9.41	14.17±10.39	14.18±10.35	14.18±10.35
Lymp.	59.59±20.11	56.10±20.71	57.05±20.03	56.57±20.33	56.50±20.33	56.50±20.33	56.50±20.33
Glass	2.44±0.00	4.11±1.96	4.05±2.20	4.67±1.55	4.71±1.76	4.71±1.76	4.71±1.76
Wilt	3.62±0.27	4.13±0.63	4.13±0.72	3.92±0.57	3.94±0.55	3.94±0.56	3.94±0.56
Lett.	7.41±0.00	7.46±0.10	7.42±0.07	6.16±0.31	6.16±0.29	6.16±0.30	6.16±0.30
Annt.	5.68±0.00	10.56±4.98	10.18±4.55	9.76±2.57	9.36±1.56	9.40±1.59	9.40±1.59
Wine	52.47±0.00	50.93±1.64	51.33±2.09	32.61±15.05	31.58±17.61	31.63±17.58	31.63±17.58
Stam.	14.35±0.00	15.00±2.04	14.94±2.07	19.11±7.18	19.33±7.92	19.35±7.86	19.36±7.86
Mnist	10.56±0.00	22.86±9.42	20.08±7.58	39.06±1.58	38.95±1.15	38.90±0.82	38.94±0.83
Page.	31.00±0.00	41.09±21.37	38.41±18.56	46.98±15.00	46.24±15.59	46.25±15.61	46.24±15.61
Vert.	8.57±0.00	11.90±3.57	11.46±3.08	9.96±1.69	10.09±1.65	10.09±1.65	10.09±1.65
Card.	23.39±0.00	29.66±4.04	29.19±4.71	47.21±8.45	47.04±6.99	47.06±6.95	47.06±6.95
WPBC	26.17±0.00	26.11±0.39	25.98±0.50	22.03±0.31	22.00±0.34	22.02±0.36	22.02±0.35
Sate.	22.86±0.00	23.18±0.23	23.09±0.17	62.72±2.36	62.03±1.35	62.07±1.41	62.07±1.41
Pima	62.14±0.00	59.93±3.58	59.58±4.06	59.64±2.21	59.58±2.41	59.57±2.40	59.57±2.40
Brea.	99.06±0.00	98.46±1.43	98.24±2.05	96.64±3.46	96.91±2.60	96.89±2.59	96.89±2.59
Iono.	25.83±0.00	26.33±0.27	26.16±0.21	68.31±1.06	68.66±0.70	68.63±0.71	68.63±0.71
Spam.	52.54±0.00	45.74±7.75	43.23±5.67	42.26±1.43	41.95±0.68	42.02±0.72	42.02±0.72
Hear.	84.10±0.00	81.66±3.86	82.29±2.92	68.07±9.17	67.77±9.62	67.77±9.64	67.77±9.63
Arrh.	53.32±0.00	53.30±0.46	53.36±0.15	74.21±0.22	74.25±0.15	74.26±0.19	74.29±0.23
Park.	94.84±0.00	93.75±0.96	94.19±0.57	73.98±3.32	73.46±3.16	73.49±3.16	73.50±3.17

Table A42: AE (Layers=3, ReLU=No, Bias=No, loss=L2, scoring=L1): AUROC and AUPRC (mean±SD, %).

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	68.40±0.00	68.72±0.78	68.47±0.88	52.73±21.48	53.44±21.04	53.45±21.07	53.45±21.08
Sati.	43.38±0.00	43.14±0.56	43.27±0.58	99.46±0.16	99.46±0.10	99.46±0.10	99.46±0.10
Shut.	85.37±0.00	85.31±0.52	85.28±0.36	87.19±5.46	87.36±4.80	87.36±4.80	87.36±4.80
WBC	98.83±0.00	98.82±0.02	98.83±0.01	98.82±0.06	98.80±0.08	98.79±0.09	98.79±0.09
Thyr.	27.85±0.00	28.13±2.38	28.32±2.68	39.02±16.58	42.01±17.85	42.03±17.82	42.03±17.82
WDBC	98.15±0.00	98.11±0.05	98.12±0.03	90.22±1.36	89.33±1.31	89.34±1.31	89.33±1.30
Optd.	61.43±0.00	61.17±0.59	61.50±0.42	52.36±3.80	52.22±1.78	52.31±1.67	52.32±1.66
Wave.	45.64±0.00	45.87±0.78	45.77±0.77	63.04±6.37	63.26±6.54	63.27±6.51	63.27±6.51
Musk	0.17±0.00	0.20±0.10	0.17±0.04	99.94±0.04	99.99±0.01	99.99±0.01	99.99±0.01
Vowe.	87.84±0.00	87.66±0.91	87.79±0.97	67.10±11.48	66.05±11.32	65.99±11.36	65.99±11.35
Lymp.	73.77±0.00	73.77±0.00	73.77±0.00	73.74±0.07	73.74±0.07	73.74±0.07	73.74±0.07
Glass	19.95±0.00	20.16±0.86	20.22±0.89	27.41±12.46	28.80±14.84	28.81±14.83	28.81±14.83
Wilt	33.26±0.00	33.23±0.11	33.24±0.10	33.15±0.27	33.16±0.31	33.16±0.31	33.16±0.31
Lett.	57.03±0.00	56.95±0.18	56.98±0.18	50.95±2.66	51.01±1.83	51.01±1.83	51.00±1.83
Annt.	38.60±0.00	38.51±0.37	38.70±0.58	55.93±6.26	55.00±5.07	55.06±5.04	55.06±5.04
Wine	96.55±0.00	96.50±0.12	96.55±0.17	76.38±19.26	78.27±19.05	78.27±19.06	78.28±19.06
Stam.	63.43±0.00	63.52±1.96	63.44±1.76	64.31±8.57	66.39±10.50	66.37±10.48	66.37±10.48
Mnist	39.78±0.00	39.86±0.39	39.64±0.36	80.34±1.96	81.63±1.03	81.64±0.97	81.62±0.99
Page.	67.65±0.00	67.61±0.12	67.64±0.08	69.23±5.43	69.21±5.40	69.20±5.40	69.20±5.40
Vert.	31.89±0.00	31.94±0.46	31.93±0.46	32.67±3.13	32.53±3.39	32.53±3.39	32.53±3.39
Card.	53.69±0.00	53.39±0.60	53.49±0.53	70.90±8.18	71.45±7.98	71.40±8.02	71.30±8.11
WPBC	56.87±0.00	56.95±0.04	56.91±0.03	51.38±0.78	51.45±0.64	51.40±0.67	51.40±0.67
Sate.	32.22±0.00	32.11±0.26	32.18±0.21	57.95±2.06	58.57±1.11	58.59±1.13	58.59±1.13
Pima	75.42±0.00	75.41±0.13	75.41±0.14	75.86±1.94	75.82±1.96	75.81±1.95	75.81±1.95
Brea.	99.52±0.00	99.52±0.00	99.52±0.00	99.43±0.21	99.42±0.21	99.42±0.21	99.42±0.21
Iono.	25.51±0.00	25.40±0.20	25.42±0.23	74.78±1.20	75.25±0.64	75.24±0.63	75.24±0.63
Spam.	68.33±0.00	68.29±0.23	68.28±0.16	60.24±0.78	60.27±0.55	60.27±0.55	60.27±0.55
Hear.	86.03±0.00	85.96±0.26	85.96±0.28	70.75±14.61	70.62±14.98	70.61±15.00	70.61±15.00
Arrh.	52.08±0.00	52.00±0.53	51.99±0.13	74.03±0.42	73.97±0.32	73.96±0.25	73.95±0.30
Park.	83.86±0.00	83.84±0.36	83.79±0.33	48.48±7.85	46.69±7.89	46.69±7.87	46.70±7.86

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.35±0.00	0.35±0.02	0.34±0.01	0.26±0.14	0.26±0.14	0.26±0.14	0.26±0.14
Sati.	1.00±0.00	1.00±0.01	1.00±0.01	95.39±0.42	95.44±0.26	95.44±0.26	95.44±0.26
Shut.	16.10±0.00	16.03±0.33	16.02±0.24	15.53±6.11	15.01±4.35	15.01±4.34	15.01±4.34
WBC	71.51±0.00	71.48±0.24	71.50±0.18	71.51±2.53	71.08±1.94	71.05±1.94	71.05±1.94
Thyr.	2.64±0.00	2.77±0.45	2.80±0.53	6.95±4.55	8.33±7.02	8.33±7.03	8.33±7.03
WDBC	76.51±0.00	76.32±0.39	76.45±0.06	44.61±4.70	42.29±4.06	42.35±4.03	42.35±4.03
Optd.	3.92±0.00	3.88±0.09	3.93±0.07	2.75±0.23	2.73±0.10	2.73±0.10	2.73±0.10
Wave.	2.57±0.00	2.60±0.06	2.59±0.05	4.27±0.81	4.32±0.81	4.32±0.81	4.32±0.81
Musk	1.60±0.00	1.60±0.00	1.60±0.00	98.17±1.46	99.76±0.36	99.80±0.25	99.80±0.25
Vowe.	39.26±0.00	37.16±2.71	37.72±3.21	10.71±8.81	9.56±8.99	9.52±8.99	9.52±8.98
Lymp.	68.15±0.00	68.15±0.00	68.15±0.00	67.77±1.13	67.77±1.13	67.77±1.13	67.77±1.13
Glass	2.44±0.00	2.44±0.02	2.44±0.02	2.91±0.80	3.09±1.12	3.09±1.12	3.09±1.12
Wilt	3.60±0.00	3.60±0.01	3.60±0.01	3.60±0.01	3.60±0.02	3.60±0.02	3.60±0.02
Lett.	7.41±0.00	7.40±0.04	7.41±0.05	6.31±0.30	6.35±0.28	6.35±0.28	6.35±0.28
Annt.	5.68±0.00	5.68±0.05	5.70±0.08	9.86±2.02	9.53±1.64	9.54±1.63	9.54±1.63
Wine	52.47±0.00	52.25±0.81	52.54±1.13	26.10±19.35	28.74±19.55	28.75±19.55	28.76±19.55
Stam.	14.35±0.00	14.41±1.02	14.35±0.84	15.41±4.63	16.55±5.92	16.56±5.95	16.55±5.94
Mnist	10.56±0.00	10.57±0.22	10.48±0.14	32.36±1.72	33.42±1.28	33.39±1.26	33.38±1.27
Page.	31.00±0.00	31.00±0.29	31.04±0.26	33.50±7.54	33.61±9.85	33.59±9.85	33.59±9.85
Vert.	8.57±0.00	8.57±0.05	8.57±0.05	8.69±0.38	8.68±0.40	8.68±0.40	8.68±0.40
Card.	23.39±0.00	23.25±0.30	23.31±0.28	44.73±6.45	45.20±6.72	45.16±6.75	45.13±6.77
WPBC	26.17±0.00	26.24±0.08	26.22±0.04	23.05±0.75	23.07±0.64	23.06±0.66	23.06±0.66
Sate.	22.86±0.00	22.83±0.07	22.85±0.06	58.61±1.13	58.79±1.23	58.80±1.25	58.80±1.25
Pima	62.14±0.00	62.13±0.14	62.13±0.15	61.65±1.98	61.64±2.16	61.63±2.17	61.63±2.17
Brea.	99.06±0.00	99.06±0.01	99.06±0.01	98.92±0.35	98.90±0.37	98.90±0.37	98.90±0.37
Iono.	25.83±0.00	25.81±0.09	25.81±0.10	66.90±0.75	67.19±0.58	67.18±0.60	67.18±0.59
Spam.	52.54±0.00	52.47±0.26	52.45±0.21	44.73±0.62	44.82±0.48	44.81±0.48	44.81±0.48
Hear.	84.10±0.00	83.96±0.39	83.97±0.43	64.94±15.31	64.31±15.23	64.27±15.22	64.28±15.22
Arrh.	53.32±0.00	53.21±0.44	53.26±0.11	74.30±0.43	74.24±0.40	74.19±0.31	74.17±0.39
Park.	94.84±0.00	94.84±0.10	94.82±0.10	77.30±4.96	76.23±5.09	76.23±5.07	76.23±5.07

Table A43: AE (Layers=3, ReLU=Yes, Bias=Yes, loss=L1, scoring=L2): AUROC and AUPRC (mean±SD, %).

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	58.54±9.60	58.18±9.59	43.90±22.40	42.31±22.71	42.29±22.71	42.29±22.72
Sati.	67.11±0.00	67.32±5.89	67.17±5.21	99.31±0.16	99.37±0.11	99.37±0.11	99.37±0.11
Shut.	86.93±0.00	89.19±7.29	88.82±6.65	86.89±9.94	86.09±9.97	86.11±9.94	86.11±9.93
WBC	98.65±0.00	94.59±11.50	94.61±11.31	98.22±0.95	98.17±1.08	98.17±1.09	98.17±1.09
Thyr.	45.04±0.00	37.74±31.24	37.78±31.86	48.79±28.96	48.84±28.70	48.85±28.71	48.85±28.71
WDBC	97.68±0.00	97.70±0.29	97.64±0.29	91.54±3.57	91.17±3.70	91.25±3.72	91.25±3.72
Optd.	59.10±0.00	47.89±22.22	52.80±19.24	61.17±3.42	62.57±1.23	62.80±1.09	62.81±1.01
Wave.	51.22±0.00	49.15±7.36	49.79±7.01	58.04±11.95	59.40±11.75	59.50±11.68	59.51±11.68
Musk	11.94±0.00	14.33±4.85	12.14±3.63	99.98±0.02	100.00±0.01	100.00±0.01	100.00±0.01
Vowe.	90.15±0.00	78.88±12.92	78.82±12.33	69.74±14.90	69.39±14.92	69.39±14.93	69.39±14.94
Lymp.	68.46±20.04	66.36±24.41	67.10±23.62	73.69±12.94	73.33±12.91	73.22±12.87	73.22±12.87
Glass	20.22±0.00	46.39±20.87	46.45±20.00	51.40±20.59	51.76±20.53	51.79±20.51	51.79±20.51
Wilt	33.69±9.81	39.63±9.60	39.29±9.50	39.01±9.69	39.18±9.45	39.17±9.46	39.18±9.46
Lett.	56.33±0.00	56.23±1.19	56.12±1.16	51.78±1.96	52.34±1.99	52.35±1.97	52.35±1.97
Annt.	44.18±0.00	50.91±14.79	48.80±14.81	43.73±8.60	44.28±9.08	44.34±9.11	44.36±9.10
Wine	95.80±0.00	93.45±2.43	93.64±2.37	83.75±16.02	83.18±17.37	83.22±17.22	83.22±17.22
Stam.	66.81±0.00	67.30±13.45	67.29±12.74	71.66±21.81	71.76±21.73	71.76±21.74	71.76±21.74
Mnist	58.28±0.00	59.05±11.66	56.62±12.19	85.11±0.71	85.71±0.11	85.67±0.07	85.70±0.07
Page.	70.92±0.00	65.04±18.99	65.52±18.58	67.35±18.56	67.54±18.58	67.54±18.59	67.53±18.59
Vert.	31.62±0.00	42.86±14.80	42.60±14.34	38.52±13.03	38.55±13.07	38.57±13.09	38.57±13.10
Card.	60.06±0.00	62.17±7.54	62.38±7.68	70.96±8.30	71.91±7.01	71.96±7.03	71.97±7.02
WPBC	56.47±0.00	55.85±0.87	55.90±0.75	50.95±2.11	50.72±1.75	50.74±1.76	50.75±1.75
Sate.	38.03±0.00	38.07±1.93	38.02±1.68	64.58±3.19	65.03±1.76	65.03±1.76	65.04±1.75
Pima	76.08±0.00	74.47±2.74	74.50±2.85	73.80±3.63	73.72±3.65	73.73±3.65	73.73±3.65
Brea.	99.53±0.00	98.19±3.67	98.37±3.12	99.02±0.77	98.94±1.03	98.93±1.03	98.93±1.03
Iono.	32.83±0.00	33.46±1.10	33.53±1.11	80.08±1.91	80.70±1.28	80.71±1.26	80.72±1.25
Spam.	60.31±0.00	58.51±7.91	57.49±9.39	57.96±0.25	58.28±0.09	58.30±0.11	58.29±0.11
Hear.	85.21±0.00	81.15±5.13	81.37±5.00	76.89±6.80	76.34±7.09	76.35±7.07	76.35±7.08
Arrh.	55.38±0.00	55.73±0.49	55.46±0.40	72.97±0.37	73.13±0.25	73.23±0.15	73.26±0.24
Park.	79.08±0.00	77.94±4.31	78.47±3.73	52.07±9.64	50.24±9.71	50.24±9.71	50.25±9.71

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.35±0.21	0.42±0.45	0.25±0.26	0.24±0.23	0.24±0.23	0.24±0.23
Sati.	1.89±0.00	2.47±1.41	2.19±0.77	95.74±0.27	95.88±0.19	95.87±0.19	95.87±0.19
Shut.	17.14±0.00	22.33±20.07	22.23±20.67	25.97±27.28	25.31±27.26	25.27±27.24	25.28±27.25
WBC	70.28±0.00	65.02±10.90	64.61±10.49	67.04±4.84	67.00±5.01	67.02±5.03	67.03±5.03
Thyr.	10.10±0.00	9.51±11.46	9.92±11.68	11.77±10.65	11.71±10.53	11.71±10.55	11.71±10.55
WDBC	70.66±0.00	72.32±3.08	71.99±3.00	51.20±13.18	49.44±13.95	49.67±14.12	49.68±14.12
Optd.	3.41±0.00	3.10±1.51	3.21±1.08	3.34±0.26	3.45±0.11	3.47±0.10	3.47±0.09
Wave.	2.88±0.00	2.86±0.56	2.90±0.56	4.12±1.36	4.26±1.29	4.26±1.28	4.27±1.28
Musk	1.72±0.00	1.81±0.15	1.75±0.09	99.22±0.79	99.86±0.24	99.84±0.30	99.84±0.30
Vowe.	39.78±0.00	26.12±19.66	25.32±19.52	14.33±9.77	13.93±9.71	13.93±9.72	13.93±9.72
Lymp.	41.28±27.72	51.28±24.82	51.26±24.61	55.30±18.15	55.32±18.16	55.30±18.15	55.30±18.15
Glass	2.45±0.00	4.83±2.72	4.73±2.57	6.51±5.60	6.53±5.56	6.51±5.56	6.51±5.56
Wilt	3.73±0.57	4.09±0.65	4.07±0.65	4.06±0.66	4.06±0.65	4.06±0.65	4.06±0.65
Lett.	7.42±0.00	7.54±0.28	7.49±0.24	6.65±0.51	6.70±0.35	6.69±0.35	6.69±0.35
Annt.	7.43±0.00	10.50±6.79	9.62±5.42	7.62±1.58	7.78±1.71	7.79±1.72	7.80±1.72
Wine	49.35±0.00	43.48±9.80	43.10±8.02	31.94±18.80	31.58±18.70	31.60±18.68	31.60±18.68
Stam.	15.64±0.00	17.57±5.45	17.39±5.11	23.22±10.23	23.10±10.20	23.09±10.20	23.09±10.20
Mnist	22.31±0.00	21.62±4.60	20.45±4.70	38.16±0.82	38.84±0.14	38.82±0.12	38.87±0.10
Page.	35.38±0.00	45.55±19.38	44.42±18.17	42.64±18.67	43.02±18.47	43.02±18.47	43.02±18.47
Vert.	8.56±0.00	11.63±4.43	11.53±4.37	10.24±2.82	10.28±2.88	10.29±2.90	10.29±2.90
Card.	28.82±0.00	32.00±5.08	32.13±5.37	43.40±7.58	44.18±6.84	44.20±6.84	44.20±6.83
WPBC	25.68±0.00	25.25±0.73	25.29±0.64	22.62±1.11	22.53±1.01	22.54±1.01	22.53±1.01
Sate.	24.44±0.00	24.63±0.85	24.56±0.66	64.80±3.14	64.59±2.25	64.57±2.23	64.59±2.23
Pima	61.69±0.00	60.15±2.35	60.19±2.64	58.94±3.17	58.84±3.21	58.84±3.20	58.85±3.20
Brea.	99.11±0.00	97.90±2.96	98.02±2.56	98.43±0.83	98.36±1.03	98.35±1.03	98.35±1.03
Iono.	30.87±0.00	31.14±0.46	31.15±0.43	70.86±2.54	71.02±1.93	71.02±1.94	71.01±1.93
Spam.	44.11±0.00	44.75±6.21	44.22±7.07	42.55±0.14	42.74±0.06	42.75±0.07	42.74±0.07
Hear.	81.29±0.00	76.16±5.76	76.55±5.73	70.87±7.87	70.13±8.16	70.15±8.15	70.15±8.15
Arrh.	56.00±0.00	56.19±0.52	56.07±0.30	70.96±0.34	71.08±0.19	71.18±0.12	71.19±0.19
Park.	93.37±0.00	92.68±1.84	92.93±1.45	79.96±5.24	78.77±5.37	78.77±5.37	78.78±5.37

Table A44: AE (Layers=3, ReLU=Yes, Bias=No, loss=L1, scoring=L2): AUROC and AUPRC (mean±SD, %).

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	66.96±0.88	67.01±0.90	57.63±17.29	57.91±17.75	57.91±17.71	57.91±17.71
Sati.	67.11±0.00	66.72±0.51	66.76±0.46	99.24±0.27	99.31±0.09	99.31±0.10	99.31±0.10
Shut.	86.93±0.00	87.38±0.86	87.34±0.84	84.46±8.10	84.98±7.20	84.98±7.23	84.98±7.23
WBC	98.65±0.00	98.66±0.05	98.66±0.05	98.48±0.23	98.47±0.21	98.47±0.20	98.47±0.20
Thyr.	45.04±0.00	45.28±0.90	45.26±0.91	52.34±8.41	53.16±9.32	53.18±9.33	53.18±9.33
WDBC	97.68±0.00	97.73±0.07	97.72±0.05	86.43±1.92	86.25±1.95	86.27±1.94	86.28±1.94
Optd.	59.10±0.00	59.46±0.88	59.58±0.95	61.49±1.87	61.72±0.69	61.72±0.65	61.73±0.66
Wave.	51.22±0.00	51.00±1.83	51.11±1.74	59.27±13.86	61.00±13.05	61.09±13.12	61.09±13.12
Musk	11.94±0.00	12.22±1.48	11.90±0.33	99.95±0.02	99.97±0.02	99.97±0.02	99.98±0.02
Vowe.	90.15±0.00	90.20±0.62	90.11±0.54	75.53±11.05	75.76±11.40	75.75±11.39	75.75±11.39
Lymp.	73.53±0.00	73.53±0.00	73.53±0.00	73.53±0.00	73.53±0.00	73.53±0.00	73.53±0.00
Glass	20.22±0.00	20.19±3.39	20.20±3.15	27.31±18.62	27.62±19.24	27.64±19.25	27.64±19.25
Wilt	32.45±0.00	32.45±0.06	32.46±0.06	32.38±0.52	32.40±0.58	32.40±0.58	32.40±0.58
Lett.	56.33±0.00	56.21±0.21	56.22±0.20	52.63±2.22	52.79±2.10	52.81±2.09	52.81±2.09
Annt.	44.18±0.00	44.25±0.38	44.37±0.31	55.09±2.65	55.12±2.70	55.00±2.75	55.00±2.75
Wine	95.80±0.00	95.78±0.18	95.83±0.16	81.00±18.01	81.59±17.60	81.59±17.58	81.57±17.59
Stam.	66.81±0.00	66.68±2.24	66.78±1.71	68.54±6.84	67.57±7.12	67.56±7.10	67.56±7.11
Mnist	58.28±0.00	58.22±0.55	58.17±0.32	84.82±0.20	85.42±0.23	85.43±0.15	85.39±0.13
Page.	70.92±0.00	70.81±0.30	70.84±0.27	72.12±2.79	72.21±2.78	72.21±2.78	72.21±2.78
Vert.	31.62±0.00	31.69±0.35	31.72±0.33	31.57±1.30	31.67±1.33	31.67±1.33	31.67±1.33
Card.	60.06±0.00	59.93±0.52	59.94±0.37	70.95±7.66	70.15±8.66	70.01±8.69	70.02±8.70
WPBC	56.47±0.00	56.48±0.12	56.47±0.08	50.80±0.79	50.89±1.20	50.93±1.29	50.92±1.26
Sate.	38.03±0.00	37.89±0.18	37.90±0.17	57.98±2.95	59.67±1.86	59.64±1.84	59.64±1.84
Pima	76.08±0.00	76.06±0.17	76.07±0.16	75.13±2.20	75.13±2.05	75.13±2.05	75.13±2.04
Brea.	99.53±0.00	99.53±0.01	99.53±0.01	99.37±0.19	99.34±0.26	99.34±0.26	99.34±0.26
Iono.	32.83±0.00	32.67±0.28	32.73±0.21	79.30±2.88	80.12±2.14	80.12±2.14	80.12±2.14
Spam.	60.31±0.00	60.29±0.07	60.28±0.06	57.44±0.58	57.74±0.35	57.74±0.35	57.74±0.35
Hear.	85.21±0.00	85.29±0.23	85.31±0.23	74.13±11.97	74.55±11.78	74.51±11.74	74.51±11.74
Arrh.	55.38±0.00	55.54±0.39	55.39±0.13	73.18±0.35	73.21±0.24	73.29±0.21	73.23±0.20
Park.	79.08±0.00	78.81±0.69	78.80±0.67	50.21±9.27	50.16±10.89	50.14±10.91	50.13±10.90

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.34±0.03	0.34±0.04	0.28±0.15	0.30±0.18	0.30±0.18	0.30±0.18
Sati.	1.89±0.00	1.84±0.07	1.84±0.06	95.84±0.46	95.93±0.09	95.93±0.09	95.93±0.09
Shut.	17.14±0.00	17.41±0.79	17.39±0.81	16.15±6.75	16.89±6.21	16.89±6.22	16.89±6.22
WBC	70.28±0.00	70.39±0.59	70.41±0.51	67.80±3.25	66.82±4.81	67.17±4.47	67.17±4.47
Thyr.	10.10±0.00	10.20±0.27	10.19±0.28	12.50±2.98	12.88±3.66	12.89±3.67	12.89±3.67
WDBC	70.66±0.00	70.86±0.39	70.84±0.37	30.71±7.51	30.59±7.31	30.76±7.43	30.75±7.43
Optd.	3.41±0.00	3.44±0.09	3.46±0.09	3.35±0.16	3.36±0.06	3.36±0.06	3.36±0.06
Wave.	2.88±0.00	2.88±0.13	2.88±0.12	4.27±1.34	4.39±1.23	4.38±1.22	4.38±1.22
Musk	1.72±0.00	1.72±0.03	1.71±0.01	98.19±0.80	98.95±0.71	99.14±0.62	99.17±0.63
Vowe.	39.78±0.00	39.25±1.88	38.81±2.67	18.63±13.93	19.09±14.17	19.08±14.15	19.08±14.15
Lymp.	64.39±0.00	64.39±0.00	64.39±0.00	64.39±0.00	64.39±0.00	64.39±0.00	64.39±0.00
Glass	2.45±0.00	2.46±0.09	2.46±0.08	3.16±1.48	3.22±1.58	3.21±1.57	3.21±1.57
Wilt	3.57±0.00	3.56±0.00	3.57±0.00	3.56±0.03	3.56±0.03	3.56±0.03	3.56±0.03
Lett.	7.42±0.00	7.38±0.05	7.40±0.06	6.61±0.20	6.59±0.20	6.58±0.22	6.58±0.22
Annt.	7.43±0.00	7.43±0.09	7.47±0.07	10.02±0.61	10.05±0.65	10.02±0.66	10.02±0.66
Wine	49.35±0.00	49.33±0.49	49.39±0.50	34.29±21.43	33.99±20.17	33.24±19.35	33.23±19.35
Stam.	15.64±0.00	15.65±1.24	15.69±0.94	17.49±3.25	17.09±3.07	17.08±3.07	17.08±3.07
Mnist	22.31±0.00	22.29±0.27	22.27±0.17	38.25±0.26	38.77±0.28	38.78±0.16	38.74±0.16
Page.	35.38±0.00	35.28±0.65	35.28±0.62	37.97±7.56	38.29±7.82	38.29±7.83	38.29±7.83
Vert.	8.56±0.00	8.56±0.04	8.57±0.04	8.56±0.15	8.57±0.15	8.57±0.15	8.57±0.15
Card.	28.82±0.00	28.73±0.44	28.71±0.30	44.72±6.50	44.54±7.05	44.47±7.04	44.48±7.04
WPBC	25.68±0.00	25.69±0.12	25.68±0.07	22.39±0.36	22.42±0.57	22.42±0.59	22.42±0.57
Sate.	24.44±0.00	24.38±0.07	24.39±0.06	58.37±1.75	58.96±0.89	58.96±0.89	58.96±0.89
Pima	61.69±0.00	61.75±0.11	61.77±0.12	59.73±2.43	59.74±2.37	59.74±2.37	59.74±2.37
Brea.	99.11±0.00	99.11±0.02	99.11±0.02	98.79±0.39	98.71±0.60	98.71±0.60	98.71±0.60
Iono.	30.87±0.00	30.89±0.14	30.93±0.09	70.38±1.70	70.64±1.28	70.64±1.28	70.63±1.28
Spam.	44.11±0.00	44.11±0.06	44.10±0.03	42.20±0.40	42.39±0.26	42.39±0.25	42.39±0.25
Hear.	81.29±0.00	81.32±0.39	81.37±0.35	66.84±12.34	67.30±12.38	67.26±12.35	67.26±12.35
Arrh.	56.00±0.00	56.02±0.22	56.01±0.11	71.06±0.34	71.20±0.16	71.20±0.14	71.16±0.17
Park.	93.37±0.00	93.27±0.22	93.27±0.22	78.20±5.98	78.05±7.01	78.04±7.02	78.04±7.01

Table A45: AE (Layers=3, ReLU=No, Bias=Yes, loss=L1, scoring=L2): AUROC and AUPRC (mean±SD, %).

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	57.78±10.66	57.95±10.57	47.16±25.20	44.94±25.41	44.94±25.39	44.94±25.39
Sati.	67.11±0.00	67.16±5.39	66.92±4.97	99.36±0.11	99.43±0.08	99.43±0.09	99.43±0.09
Shut.	86.93±0.00	90.57±6.61	90.39±6.45	88.78±8.08	88.67±8.22	88.67±8.22	88.67±8.22
WBC	98.65±0.00	94.57±11.73	94.66±11.33	98.29±0.53	98.32±0.45	98.31±0.46	98.31±0.46
Thyr.	45.04±0.00	39.34±31.16	38.45±31.34	55.08±30.90	55.73±31.14	55.69±31.10	55.70±31.11
WDBC	97.68±0.00	97.63±0.38	97.62±0.33	91.73±1.93	91.27±2.14	91.23±2.22	91.22±2.22
Optd.	59.10±0.00	48.21±21.46	51.80±18.95	61.55±2.96	62.52±0.87	62.51±0.76	62.48±0.75
Wave.	51.22±0.00	48.71±8.18	49.37±7.93	58.98±9.61	60.71±9.73	60.72±9.70	60.72±9.70
Musk	11.94±0.00	15.08±3.55	12.86±3.70	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
Vowe.	90.15±0.00	79.26±12.72	79.24±11.94	66.66±16.58	65.80±15.92	65.81±15.92	65.81±15.92
Lymp.	68.46±20.04	66.37±24.42	67.10±23.62	73.71±12.95	73.31±12.91	73.35±12.91	73.35±12.91
Glass	20.22±0.00	45.76±21.53	45.66±20.77	52.52±23.00	52.72±23.04	52.71±23.07	52.72±23.07
Wilt	33.69±9.81	39.41±9.82	38.99±9.67	38.05±9.41	38.25±9.26	38.25±9.27	38.25±9.27
Lett.	56.33±0.00	56.10±1.19	56.00±1.10	52.77±1.71	53.37±1.42	53.40±1.45	53.40±1.45
Annt.	44.18±0.00	52.03±14.12	49.78±13.43	45.11±10.81	44.41±10.84	44.41±10.83	44.43±10.83
Wine	95.80±0.00	93.35±2.60	93.50±2.55	76.66±19.30	73.61±23.11	73.66±23.09	73.67±23.10
Stam.	66.81±0.00	68.04±12.79	68.14±11.36	70.92±22.17	71.14±22.60	71.12±22.63	71.11±22.64
Mnist	58.28±0.00	57.90±11.11	55.48±11.12	85.57±1.03	85.68±0.15	85.70±0.07	85.70±0.12
Page.	70.92±0.00	64.16±17.93	64.89±17.26	66.82±17.59	66.72±17.46	66.72±17.47	66.72±17.47
Vert.	31.62±0.00	42.30±14.28	42.28±14.00	38.14±10.73	38.30±10.88	38.30±10.88	38.30±10.88
Card.	60.06±0.00	62.90±8.04	62.92±8.24	71.26±8.25	72.70±6.66	72.63±6.54	72.64±6.54
WPBC	56.47±0.00	55.84±0.91	55.93±0.70	50.62±1.77	50.21±1.28	50.24±1.29	50.24±1.29
Sate.	38.03±0.00	38.00±1.79	37.92±1.62	65.64±2.10	65.04±1.26	65.05±1.21	65.05±1.21
Pima	76.08±0.00	74.48±2.59	74.49±2.77	74.17±3.26	74.06±3.38	74.07±3.39	74.07±3.39
Brea.	99.53±0.00	98.20±3.62	98.46±2.83	98.88±0.78	98.80±0.98	98.80±0.97	98.80±0.97
Iono.	32.83±0.00	33.51±1.24	33.53±1.24	81.11±1.12	81.57±0.45	81.58±0.46	81.58±0.46
Spam.	60.31±0.00	58.79±8.54	57.92±9.07	57.88±0.31	58.19±0.15	58.19±0.15	58.19±0.15
Hear.	85.21±0.00	80.98±5.30	81.21±5.14	72.18±8.75	71.48±8.95	71.43±8.98	71.43±8.98
Arrh.	55.38±0.00	55.75±0.67	55.51±0.53	73.23±0.38	73.07±0.51	73.14±0.25	73.11±0.16
Park.	79.08±0.00	77.46±4.72	78.12±4.07	47.28±6.26	45.66±5.93	45.74±5.94	45.75±5.93

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.33±0.20	0.37±0.33	0.31±0.35	0.27±0.26	0.27±0.26	0.27±0.26
Sati.	1.89±0.00	2.38±1.43	2.11±0.70	95.88±0.14	95.98±0.13	95.98±0.13	95.98±0.13
Shut.	17.14±0.00	24.56±20.12	24.38±20.90	27.69±27.36	27.54±27.18	27.51±27.17	27.51±27.17
WBC	70.28±0.00	64.31±10.82	64.31±10.38	65.79±6.11	66.00±5.49	65.88±5.69	65.85±5.69
Thyr.	10.10±0.00	9.68±11.23	9.94±11.38	16.09±13.56	16.32±13.43	16.30±13.43	16.31±13.45
WDBC	70.66±0.00	71.79±3.56	71.95±3.54	50.50±10.72	48.88±10.98	48.56±11.40	48.57±11.40
Optd.	3.41±0.00	3.14±1.65	3.16±1.19	3.37±0.23	3.44±0.08	3.44±0.07	3.44±0.07
Wave.	2.88±0.00	2.85±0.62	2.90±0.64	4.18±0.98	4.39±0.97	4.38±0.96	4.38±0.96
Musk	1.72±0.00	1.82±0.11	1.77±0.10	99.97±0.07	100.00±0.00	100.00±0.00	100.00±0.00
Vowe.	39.78±0.00	26.60±19.63	25.14±19.83	13.33±10.09	11.95±9.51	11.97±9.51	11.97±9.51
Lymp.	41.28±27.72	51.28±24.82	51.26±24.61	55.31±18.15	55.31±18.16	55.32±18.16	55.32±18.16
Glass	2.45±0.00	4.87±2.88	4.71±2.67	6.79±5.78	6.84±5.85	6.83±5.87	6.83±5.87
Wilt	3.73±0.57	4.12±0.79	4.08±0.78	4.02±0.77	4.04±0.76	4.04±0.77	4.04±0.77
Lett.	7.42±0.00	7.50±0.29	7.49±0.25	6.64±0.39	6.66±0.27	6.67±0.27	6.67±0.27
Annt.	7.43±0.00	10.55±6.32	9.53±4.91	7.96±2.03	7.85±1.99	7.87±1.98	7.87±1.98
Wine	49.35±0.00	43.23±10.06	43.57±10.08	25.61±16.79	23.62±14.74	23.64±14.76	23.67±14.78
Stam.	15.64±0.00	18.12±5.67	17.94±5.27	24.39±13.13	24.67±13.45	24.67±13.47	24.67±13.47
Mnist	22.31±0.00	20.70±4.46	19.64±3.91	38.79±1.27	38.83±0.21	38.86±0.13	38.86±0.19
Page.	35.38±0.00	44.48±18.61	43.50±17.39	42.67±17.63	42.86±17.87	42.88±17.89	42.88±17.88
Vert.	8.56±0.00	11.24±3.77	11.26±3.84	9.90±2.26	9.93±2.30	9.93±2.30	9.93±2.30
Card.	28.82±0.00	32.70±5.78	32.69±6.03	44.43±6.72	45.44±6.27	45.37±6.15	45.37±6.16
WPBC	25.68±0.00	25.28±0.84	25.33±0.70	22.47±0.79	22.29±0.62	22.32±0.63	22.32±0.63
Sate.	24.44±0.00	24.58±0.82	24.50±0.63	65.17±2.78	64.02±1.84	64.01±1.82	64.01±1.82
Pima	61.69±0.00	60.16±2.18	60.16±2.56	59.17±2.84	58.98±3.03	58.99±3.02	58.99±3.02
Brea.	99.11±0.00	97.89±2.91	98.07±2.38	98.14±0.88	98.05±1.04	98.05±1.04	98.05±1.04
Iono.	30.87±0.00	31.18±0.50	31.17±0.44	71.74±1.02	71.73±0.99	71.77±0.97	71.78±0.96
Spam.	44.11±0.00	45.00±6.64	44.45±7.01	42.50±0.18	42.67±0.09	42.68±0.09	42.68±0.09
Hear.	81.29±0.00	75.87±6.03	76.20±5.90	65.90±9.42	65.10±9.68	65.08±9.73	65.08±9.73
Arrh.	56.00±0.00	56.19±0.69	56.11±0.45	71.02±0.33	71.03±0.34	71.14±0.18	71.08±0.14
Park.	93.37±0.00	92.50±1.96	92.80±1.56	77.31±4.21	76.19±4.00	76.24±4.02	76.24±4.02

Table A46: AE (Layers=3, ReLU=No, Bias=No, loss=L1, scoring=L2): AUROC and AUPRC (mean±SD, %).

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	66.78±0.00	67.22±1.61	67.14±1.48	56.85±15.24	57.76±14.08	57.77±14.08	57.77±14.08
Sati.	67.11±0.00	67.14±0.85	67.13±0.84	99.31±0.30	99.32±0.09	99.32±0.09	99.32±0.09
Shut.	86.93±0.00	87.31±1.16	87.22±1.18	81.97±14.85	82.29±14.32	82.29±14.32	82.29±14.33
WBC	98.65±0.00	98.64±0.07	98.65±0.06	98.42±0.21	98.41±0.23	98.41±0.22	98.41±0.22
Thyr.	45.04±0.00	45.91±2.25	46.06±2.69	59.40±13.68	61.62±14.21	61.64±14.21	61.64±14.21
WDBC	97.68±0.00	97.74±0.10	97.71±0.08	86.71±1.52	85.95±1.18	85.91±1.15	85.92±1.15
Optd.	59.10±0.00	59.76±1.20	59.83±1.01	60.85±1.52	62.27±0.67	62.25±0.68	62.25±0.68
Wave.	51.22±0.00	50.61±2.87	50.77±2.62	64.13±10.13	63.98±10.60	64.03±10.53	64.03±10.54
Musk	11.94±0.00	11.96±2.07	11.91±0.73	99.98±0.02	100.00±0.00	100.00±0.00	100.00±0.00
Vowe.	90.15±0.00	89.88±0.78	89.79±1.09	67.40±12.15	67.33±11.64	67.33±11.62	67.32±11.62
Lymp.	73.53±0.00	73.56±0.07	73.56±0.07	73.54±0.04	73.51±0.07	73.51±0.07	73.51±0.07
Glass	20.22±0.00	20.64±4.64	20.36±4.10	32.21±21.46	33.19±22.15	33.23±22.16	33.23±22.16
Wilt	32.45±0.00	32.43±0.08	32.45±0.08	32.39±0.52	32.41±0.59	32.41±0.59	32.41±0.59
Lett.	56.33±0.00	56.26±0.33	56.27±0.26	53.37±2.36	53.21±1.31	53.22±1.31	53.22±1.32
Annt.	44.18±0.00	44.02±0.50	44.23±0.51	53.33±5.64	53.01±6.11	53.01±6.09	53.01±6.09
Wine	95.80±0.00	95.66±0.28	95.70±0.27	77.61±19.73	77.56±19.77	77.72±19.68	77.93±19.57
Stam.	66.81±0.00	66.42±2.64	66.63±2.09	65.50±9.61	66.23±11.06	66.27±11.05	66.27±11.05
Mnist	58.28±0.00	58.11±0.58	58.16±0.44	84.94±0.14	85.38±0.21	85.40±0.22	85.42±0.18
Page.	70.92±0.00	70.72±0.32	70.79±0.22	72.52±3.55	72.68±3.16	72.68±3.16	72.68±3.16
Vert.	31.62±0.00	31.71±0.49	31.73±0.46	32.22±3.15	32.24±3.42	32.25±3.43	32.25±3.43
Card.	60.06±0.00	59.57±0.91	59.69±0.69	71.32±8.13	70.13±8.55	70.11±8.54	70.11±8.54
WPBC	56.47±0.00	56.52±0.10	56.50±0.05	50.37±0.55	50.45±0.58	50.45±0.59	50.46±0.59
Sate.	38.03±0.00	38.04±0.33	38.05±0.29	59.41±3.11	60.54±2.31	60.54±2.31	60.54±2.31
Pima	76.08±0.00	76.10±0.25	76.11±0.24	75.71±2.26	75.58±2.27	75.58±2.27	75.58±2.27
Brea.	99.53±0.00	99.52±0.02	99.52±0.02	99.20±0.24	99.17±0.31	99.17±0.31	99.17±0.31
Iono.	32.83±0.00	32.68±0.37	32.66±0.33	79.80±1.22	80.71±0.46	80.65±0.45	80.65±0.45
Spam.	60.31±0.00	60.29±0.12	60.28±0.11	57.42±0.26	57.68±0.18	57.68±0.18	57.68±0.18
Hear.	85.21±0.00	85.13±0.38	85.17±0.35	68.97±15.12	69.55±14.91	69.51±14.87	69.51±14.87
Arrh.	55.38±0.00	55.58±0.55	55.37±0.18	73.29±0.35	72.99±0.40	73.12±0.24	73.26±0.21
Park.	79.08±0.00	78.93±0.67	78.91±0.60	47.34±10.27	46.36±11.17	46.33±11.16	46.33±11.17

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.34±0.00	0.35±0.06	0.35±0.05	0.25±0.10	0.25±0.09	0.25±0.09	0.25±0.09
Sati.	1.89±0.00	1.90±0.10	1.89±0.10	95.78±0.66	95.90±0.23	95.90±0.23	95.90±0.23
Shut.	17.14±0.00	17.70±1.38	17.45±1.11	18.63±15.33	18.54±15.68	18.54±15.68	18.54±15.68
WBC	70.28±0.00	70.19±0.78	70.25±0.71	66.56±3.46	66.09±4.89	66.12±4.89	66.12±4.89
Thyr.	10.10±0.00	10.35±0.63	10.39±0.77	16.78±10.13	18.40±12.65	18.41±12.67	18.42±12.67
WDBC	70.66±0.00	71.20±0.66	70.98±0.61	32.14±7.38	28.59±5.14	28.57±5.12	28.57±5.12
Optd.	3.41±0.00	3.48±0.12	3.48±0.10	3.29±0.13	3.41±0.06	3.41±0.06	3.41±0.06
Wave.	2.88±0.00	2.86±0.20	2.86±0.19	4.63±0.99	4.62±1.05	4.62±1.05	4.62±1.05
Musk	1.72±0.00	1.71±0.04	1.71±0.02	99.40±0.54	99.96±0.05	99.94±0.16	99.98±0.03
Vowe.	39.78±0.00	37.23±4.27	37.16±5.53	11.37±8.75	10.88±8.26	10.87±8.24	10.86±8.24
Lymp.	64.39±0.00	64.76±1.13	64.76±1.13	64.76±1.12	64.39±0.01	64.39±0.01	64.39±0.01
Glass	2.45±0.00	2.48±0.14	2.47±0.11	3.51±1.67	3.62±1.77	3.62±1.78	3.62±1.78
Wilt	3.57±0.00	3.56±0.00	3.56±0.00	3.56±0.03	3.56±0.03	3.56±0.03	3.56±0.03
Lett.	7.42±0.00	7.37±0.08	7.39±0.06	6.71±0.25	6.64±0.25	6.65±0.25	6.65±0.25
Annt.	7.43±0.00	7.39±0.11	7.43±0.10	9.69±1.20	9.67±1.27	9.66±1.26	9.66±1.27
Wine	49.35±0.00	49.10±1.02	49.20±0.70	28.41±19.37	28.09±18.47	28.17±18.50	28.24±18.43
Stam.	15.64±0.00	15.57±1.47	15.66±1.18	16.87±3.12	17.51±3.72	17.53±3.74	17.53±3.74
Mnist	22.31±0.00	22.25±0.26	22.27±0.21	38.40±0.18	38.68±0.26	38.71±0.28	38.73±0.23
Page.	35.38±0.00	35.07±0.75	35.18±0.57	38.57±6.94	38.99±6.56	38.97±6.57	38.97±6.57
Vert.	8.56±0.00	8.56±0.05	8.57±0.05	8.65±0.37	8.64±0.41	8.65±0.41	8.65±0.41
Card.	28.82±0.00	28.52±0.71	28.53±0.61	45.41±7.26	44.66±7.45	44.64±7.45	44.64±7.45
WPBC	25.68±0.00	25.71±0.12	25.69±0.06	22.24±0.24	22.23±0.25	22.23±0.26	22.24±0.26
Sate.	24.44±0.00	24.44±0.12	24.45±0.11	58.98±1.97	59.23±1.21	59.22±1.21	59.22±1.21
Pima	61.69±0.00	61.79±0.20	61.78±0.20	60.12±2.31	59.97±2.46	59.97±2.46	59.97±2.46
Brea.	99.11±0.00	99.10±0.03	99.10±0.03	98.44±0.52	98.34±0.72	98.34±0.72	98.34±0.72
Iono.	30.87±0.00	30.92±0.19	30.92±0.18	70.22±0.75	70.65±0.72	70.55±0.67	70.55±0.67
Spam.	44.11±0.00	44.10±0.10	44.10±0.08	42.18±0.20	42.35±0.13	42.35±0.13	42.35±0.13
Hear.	81.29±0.00	81.04±0.60	81.07±0.56	62.03±14.24	62.26±14.23	62.23±14.18	62.22±14.18
Arrh.	56.00±0.00	56.12±0.49	55.96±0.16	71.12±0.29	70.97±0.34	71.14±0.17	71.17±0.18
Park.	93.37±0.00	93.31±0.21	93.30±0.19	76.35±6.66	75.68±7.18	75.67±7.18	75.67±7.18

Table A47: AE (Layers=3, ReLU=Yes, Bias=Yes, loss=L2, scoring=L1): AUROC and AUPRC (mean±SD, %).

AUROC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	68.40±0.00	68.47±0.80	68.19±0.86	61.27±19.23	59.95±18.40	59.96±18.40	59.92±18.46
Sati.	43.38±0.00	50.49±3.82	48.87±2.34	99.09±0.12	99.15±0.12	99.15±0.15	99.17±0.10
Shut.	85.37±0.00	86.07±2.54	86.15±2.35	87.57±3.13	87.92±3.52	88.01±3.55	88.01±3.55
WBC	98.83±0.00	96.41±5.91	95.00±10.09	98.43±1.01	98.50±0.79	98.50±0.79	98.50±0.79
Thyr.	27.85±0.00	46.58±33.81	46.57±33.22	64.33±28.55	62.27±30.41	62.18±30.47	62.18±30.48
WDBC	98.15±0.00	97.86±0.47	97.92±0.30	90.17±3.36	89.90±2.96	89.79±2.93	89.80±2.92
Optd.	61.43±0.00	52.28±19.55	51.77±20.18	47.97±5.36	49.57±1.60	49.91±1.29	49.91±1.28
Wave.	45.64±0.00	45.71±1.40	45.82±0.95	57.80±8.50	59.12±8.08	59.11±8.02	59.11±8.02
Musk	0.17±0.00	3.12±3.77	1.29±1.09	99.86±0.09	99.92±0.06	99.91±0.06	99.92±0.06
Vowe.	87.84±0.00	86.72±1.73	87.41±1.29	72.27±11.29	72.39±11.33	72.40±11.35	72.40±11.35
Lymp.	70.41±22.62	69.84±23.13	70.36±22.79	71.28±22.00	71.20±22.30	71.20±22.30	71.20±22.30
Glass	19.95±0.00	36.02±19.22	36.77±19.57	45.22±16.49	42.94±15.67	42.80±15.69	42.80±15.69
Wilt	33.16±4.76	39.60±9.33	38.79±9.57	37.21±9.87	37.79±10.16	37.77±10.18	37.77±10.18
Lett.	57.03±0.00	56.99±0.28	56.97±0.22	49.31±1.49	49.40±1.94	49.43±1.90	49.36±1.77
Annt.	38.60±0.00	53.24±13.75	52.34±12.97	55.22±7.61	57.37±6.51	57.04±6.58	57.04±6.59
Wine	96.55±0.00	96.15±0.35	96.19±0.36	90.57±6.90	89.66±8.78	89.58±8.89	89.58±8.89
Stam.	63.43±0.00	64.87±5.31	64.46±5.43	71.86±8.58	71.65±7.30	71.56±7.20	71.56±7.20
Mnist	39.78±0.00	59.51±13.90	57.26±14.03	85.45±0.96	85.63±0.41	85.52±0.49	85.51±0.49
Page.	67.65±0.00	59.76±19.66	59.15±19.45	72.38±16.36	72.35±16.54	72.35±16.56	72.34±16.56
Vert.	31.89±0.00	46.74±12.81	44.98±11.00	42.53±10.79	43.06±10.33	43.10±10.33	43.10±10.33
Card.	53.69±0.00	59.05±5.34	59.27±6.59	75.27±3.61	74.34±2.61	74.49±2.58	74.62±2.62
WPBC	56.87±0.00	56.81±0.24	56.67±0.56	48.96±1.71	49.36±1.32	49.39±1.37	49.39±1.37
Sate.	32.22±0.00	33.33±0.80	33.01±0.53	64.63±2.06	64.29±2.05	64.32±2.10	64.28±2.13
Pima	75.42±0.00	74.19±3.44	74.01±3.39	74.48±2.35	74.59±2.25	74.60±2.24	74.59±2.24
Brea.	99.52±0.00	98.92±1.45	98.58±2.42	97.29±4.02	97.51±3.81	97.52±3.81	97.52±3.81
Iono.	25.51±0.00	26.51±0.37	26.27±0.36	75.56±1.55	75.47±1.40	75.49±1.41	75.49±1.41
Spam.	68.33±0.00	57.35±7.85	54.64±8.86	56.38±1.87	56.46±1.11	56.42±1.09	56.40±1.12
Hear.	86.03±0.00	84.59±3.49	85.24±2.55	76.07±10.58	75.65±11.13	75.63±11.16	75.63±11.16
Arrh.	52.08±0.00	52.09±0.35	52.09±0.17	74.23±0.32	73.93±0.21	73.90±0.23	73.90±0.23
Park.	83.86±0.00	81.20±2.13	82.03±1.49	46.08±9.19	45.15±9.79	45.05±9.74	45.04±9.74

AUPRC

Dataset	$d=0$	$d=1$	$d=2$	$d=3$	$d=4$	$d=5$	$d=6$
PenD.	0.35±0.00	0.35±0.02	0.35±0.02	0.34±0.17	0.31±0.15	0.31±0.15	0.31±0.15
Sati.	1.00±0.00	1.13±0.08	1.10±0.04	94.40±0.37	94.63±0.25	94.63±0.31	94.66±0.24
Shut.	16.10±0.00	14.43±2.09	15.36±1.74	13.68±2.99	14.36±3.20	14.38±3.18	14.38±3.18
WBC	71.51±0.00	66.70±9.07	67.06±9.94	70.36±2.98	70.38±3.01	70.38±3.01	70.38±3.01
Thyr.	2.64±0.00	16.55±21.95	16.38±21.30	16.95±17.74	16.76±18.20	16.75±18.21	16.75±18.21
WDBC	76.51±0.00	75.84±2.97	75.97±1.54	53.49±9.55	51.13±10.70	49.52±12.33	50.45±10.66
Optd.	3.92±0.00	3.24±1.22	3.40±1.89	2.51±0.24	2.57±0.09	2.58±0.07	2.58±0.07
Wave.	2.57±0.00	2.58±0.09	2.58±0.07	3.84±1.03	3.97±1.04	3.97±1.03	3.97±1.03
Musk	1.60±0.00	1.62±0.04	1.61±0.01	95.85±2.44	97.63±1.59	97.53±1.70	97.54±1.67
Vowe.	39.26±0.00	31.79±7.65	33.97±7.32	11.03±6.59	11.30±7.53	11.31±7.55	11.31±7.55
Lymp.	59.59±20.11	56.10±20.71	57.05±20.03	56.52±20.31	56.50±20.33	56.50±20.33	56.50±20.33
Glass	2.44±0.00	3.85±2.10	4.00±2.26	4.46±1.51	4.35±1.58	4.34±1.58	4.34±1.58
Wilt	3.62±0.27	4.09±0.64	4.04±0.65	3.94±0.63	3.98±0.65	3.98±0.65	3.98±0.65
Lett.	7.41±0.00	7.44±0.09	7.42±0.07	6.06±0.19	6.10±0.31	6.10±0.31	6.09±0.29
Annt.	5.68±0.00	10.45±5.29	10.08±4.66	9.59±2.93	9.88±2.66	9.78±2.69	9.78±2.69
Wine	52.47±0.00	50.82±1.56	50.91±1.84	40.67±17.14	40.40±17.67	40.22±17.89	40.22±17.89
Stam.	14.35±0.00	14.55±1.44	14.52±1.39	18.34±4.74	18.05±3.37	17.98±3.26	17.98±3.26
Mnist	10.56±0.00	21.99±9.48	20.07±7.99	39.11±1.76	39.25±0.59	39.10±0.73	39.09±0.74
Page.	31.00±0.00	41.80±21.47	40.03±19.67	48.24±15.33	48.31±15.80	48.33±15.80	48.33±15.80
Vert.	8.57±0.00	11.82±3.42	11.15±2.88	10.70±2.96	10.76±2.95	10.77±2.96	10.77±2.96
Card.	23.39±0.00	28.91±2.99	29.04±4.03	44.23±4.13	43.46±2.85	43.59±3.04	43.70±3.18
WPBC	26.17±0.00	26.04±0.26	25.96±0.42	21.85±0.71	21.99±0.61	22.00±0.62	22.00±0.62
Sate.	22.86±0.00	23.15±0.20	23.06±0.14	62.89±2.20	62.41±1.79	62.44±1.84	62.41±1.86
Pima	62.14±0.00	59.92±3.62	59.55±4.11	59.39±2.29	59.51±2.35	59.51±2.35	59.51±2.35
Brea.	99.06±0.00	98.43±1.45	98.18±2.17	96.97±3.62	97.17±3.38	97.18±3.38	97.18±3.38
Iono.	25.83±0.00	26.24±0.24	26.11±0.18	67.79±1.73	67.70±1.44	67.72±1.45	67.71±1.44
Spam.	52.54±0.00	44.78±7.06	42.90±6.83	42.17±1.13	42.11±0.74	42.08±0.71	42.07±0.73
Hear.	84.10±0.00	81.77±4.05	82.43±3.06	72.25±10.84	72.00±11.17	71.95±11.20	71.96±11.20
Arrh.	53.32±0.00	53.23±0.30	53.32±0.13	74.47±0.36	74.28±0.20	74.20±0.27	74.20±0.27
Park.	94.84±0.00	93.98±0.70	94.29±0.46	77.87±5.02	77.15±5.22	77.09±5.19	77.09±5.20

Table A48: AUROC and AUPRC (%) for the second baseline group. LOF, OCSVM, IForest, KNN, ECOD, MGBOD, ODHD, and LDGOD are evaluated in a single run using their default parameters; ICL, DeepSVDD, DIF, SLAD, RCA, and NeuTraL report mean ± SD over ten seeds.

AUROC: detectors 1–7

Dataset	LOF	OCSVM	IForest	KNN	ECOD	MGBOD	ODHD
PenD.	90.90	16.88	76.04	97.57	53.22	86.61	30.86
Sati.	47.02	97.68	99.20	99.31	96.49	88.34	2.21
Shut.	99.00	94.61	86.48	98.62	72.27	83.30	8.14
WBC	92.32	98.40	98.83	98.33	98.90	97.36	1.78
Thyr.	75.71	95.71	97.48	96.56	97.71	93.99	1.87
WDBC	91.15	91.15	94.23	92.80	91.74	84.06	3.19
Optd.	50.30	47.65	71.05	36.89	60.45	20.34	11.44
Wave.	73.15	55.26	71.83	74.39	60.84	73.21	30.76
Musk	60.19	100.00	100.00	97.75	95.59	61.43	0.06
Vowe.	93.74	63.52	75.21	95.22	59.29	77.69	29.61
Lymp.	79.05	86.09	84.80	84.80	81.63	81.75	18.84
Glass	76.91	49.21	79.24	77.40	70.46	73.71	17.02
Wilt	66.62	32.23	45.45	51.55	39.40	33.60	43.99
Lett.	87.61	50.68	63.07	81.95	57.23	58.70	41.06
Annt.	68.34	57.98	62.41	64.34	72.91	48.21	34.47
Wine	91.34	71.76	81.93	92.52	73.28	89.66	10.34
Stam.	72.69	87.43	88.19	90.74	87.61	92.62	10.07
Mnist	71.56	84.20	73.22	87.07	74.63	8.65	38.66
Page.	75.68	90.95	89.69	92.02	91.39	85.64	35.08
Vert.	40.24	40.19	34.33	32.24	42.00	24.54	78.40
Card.	51.95	77.03	67.57	50.79	78.53	82.23	52.45
WPBC	51.28	47.48	49.19	51.24	48.13	51.54	43.79
Sate.	55.43	59.26	72.67	71.93	58.30	60.64	19.07
Pima	62.74	60.26	67.33	71.97	59.44	70.40	41.30
Brea.	47.49	76.94	98.74	98.21	99.14	98.63	1.45
Iono.	88.83	75.24	85.05	87.28	72.84	82.67	65.58
Spam.	43.17	54.01	60.39	56.46	65.56	55.22	31.33
Hear.	55.28	57.06	61.56	65.68	60.83	70.32	31.19
Arrh.	73.10	72.79	74.52	73.75	75.27	73.36	26.42
Park.	53.74	64.30	50.81	48.60	60.25	31.41	26.45

Table A48 (continued)

AUROC: detectors 8–14

Dataset	LDGOD	ICL	DeepSVDD	DIF	SLAD	RCA	NeuTraL
PenD.	98.13	63.95±11.00	59.06±9.41	86.01±2.39	95.48±1.89	49.84±6.54	75.37±7.05
Sati.	96.20	12.79±6.68	50.77±5.36	99.83±0.03	91.02±3.51	98.54±0.17	71.76±14.23
Shut.	98.72	50.05±21.87	67.39±8.59	98.77±0.10	95.75±5.93	72.12±4.08	97.44±1.68
WBC	98.31	78.19±16.16	83.34±7.18	97.76±0.20	97.51±0.98	98.08±0.11	89.53±1.52
Thyr.	96.36	53.51±9.90	81.26±6.56	96.64±0.23	69.28±12.40	91.83±0.57	89.24±8.85
WDBC	92.16	76.04±12.22	58.54±5.04	92.15±0.67	62.46±7.40	91.38±2.43	82.39±2.21
Optd.	39.85	70.56±7.60	49.45±16.89	55.75±3.04	68.72±5.42	50.15±3.28	50.66±9.74
Wave.	74.49	39.15±3.15	50.88±3.64	73.51±1.82	52.41±1.38	62.39±2.93	56.57±6.75
Musk	76.79	68.16±13.63	54.79±18.73	99.98±0.02	95.14±2.77	97.26±0.34	86.10±8.34
Vowe.	97.38	69.00±5.91	65.50±4.33	88.59±0.90	92.14±1.89	75.83±1.38	71.82±5.55
Lymp.	83.04	54.56±10.66	81.60±6.86	82.59±1.50	88.80±5.14	79.64±2.30	85.49±2.04
Glass	86.45	44.25±9.98	74.55±9.59	81.17±0.87	77.38±4.71	58.61±4.58	83.33±1.65
Wilt	62.57	65.03±4.06	56.51±10.07	38.01±0.98	67.12±6.10	40.51±1.57	67.96±22.71
Lett.	88.42	50.06±1.73	57.22±4.65	69.30±0.94	87.16±0.80	54.28±2.03	70.41±5.08
Annt.	69.85	45.82±8.38	57.71±18.21	58.74±0.44	49.94±7.52	54.59±0.78	53.03±4.12
Wine	84.71	59.72±8.38	46.48±8.34	71.91±2.57	53.97±10.45	82.20±4.50	33.71±9.16
Stam.	87.13	20.27±6.03	67.20±6.81	87.06±0.52	28.24±7.56	73.30±3.45	77.69±3.67
Mnist	84.36	61.24±3.51	56.31±16.14	85.26±0.46	86.95±2.30	80.92±0.87	60.99±7.06
Page.	79.77	36.22±8.01	57.11±15.25	93.22±0.35	56.61±4.68	82.48±0.70	79.29±13.13
Vert.	36.24	47.50±4.50	45.13±5.70	37.13±1.58	45.96±5.35	35.85±2.53	46.90±3.31
Card.	50.45	35.51±4.62	54.62±7.60	62.53±0.83	25.96±1.97	70.02±0.92	58.22±9.80
WPBC	52.49	51.37±3.80	42.90±3.16	49.98±1.28	50.11±2.56	52.54±1.69	46.90±2.65
Sate.	67.74	49.48±4.50	55.14±4.14	71.25±1.21	62.23±3.06	52.51±1.31	60.62±1.93
Pima	71.35	43.26±3.35	48.06±4.96	69.09±0.56	48.21±2.76	69.62±1.13	58.86±3.25
Brea.	97.64	50.68±14.98	56.96±7.83	97.20±0.16	82.74±9.22	98.49±0.06	74.53±2.33
Iono.	92.25	22.75±4.28	58.72±7.24	90.12±0.39	85.14±5.83	71.18±1.24	93.32±0.54
Spam.	53.24	53.67±9.26	43.56±6.92	54.84±0.53	38.98±3.24	55.65±0.49	53.06±4.11
Hear.	64.28	50.89±5.13	49.67±3.30	61.99±1.68	56.17±3.93	69.55±1.62	48.82±2.75
Arrh.	73.61	61.82±6.87	59.37±5.15	73.51±0.23	52.78±5.55	52.58±3.72	66.34±2.43
Park.	56.62	52.62±10.00	54.81±6.46	49.36±2.44	62.24±3.82	52.00±2.42	44.12±4.91

Table A48 (continued)

AUPRC: detectors 1–7

Dataset	LOF	OCSVM	IForest	KNN	ECOD	MGBOD	ODHD
PenD.	1.18	0.11	0.39	3.89	0.20	0.71	0.14
Sati.	2.34	86.95	90.14	64.18	65.79	5.17	0.62
Shut.	36.38	16.35	5.49	32.03	3.12	3.45	0.67
WBC	11.94	67.68	71.44	65.50	71.02	29.48	1.12
Thyr.	9.32	35.72	48.64	38.56	45.93	23.98	1.25
WDBC	64.42	59.23	71.56	58.65	57.22	12.18	1.39
Optd.	3.07	2.46	4.72	2.06	3.32	1.67	1.55
Wave.	8.87	3.82	6.28	11.71	4.00	6.24	1.90
Musk	24.79	100.00	100.00	71.15	48.91	3.65	1.60
Vowe.	36.02	8.20	20.69	43.64	7.40	10.39	2.21
Lymp.	8.72	67.44	42.86	65.63	39.41	11.11	2.29
Glass	9.87	6.31	11.26	9.06	17.71	7.92	2.48
Wilt	7.50	3.58	4.41	4.94	4.12	3.64	6.63
Lett.	38.90	7.45	8.38	20.21	7.47	8.05	4.83
Annt.	13.21	10.56	11.06	12.50	19.91	6.92	5.39
Wine	30.07	16.49	18.04	36.27	16.59	26.66	4.18
Stam.	19.43	28.45	28.04	32.92	29.49	53.02	5.04
Mnist	28.04	37.87	19.68	41.07	17.73	4.96	6.85
Page.	33.51	53.40	46.18	56.08	51.95	26.56	7.25
Vert.	9.66	9.63	8.74	8.53	10.16	7.79	33.34
Card.	26.73	48.69	42.11	32.66	50.46	58.18	23.69
WPBC	22.24	21.55	21.60	22.58	21.08	22.95	19.62
Sate.	38.43	58.55	68.24	58.00	52.60	50.57	19.99
Pima	42.68	44.34	49.91	51.85	46.18	48.43	31.29
Brea.	30.62	79.65	97.15	94.55	98.39	97.47	20.12
Iono.	84.26	73.80	80.24	82.73	64.44	71.66	42.99
Spam.	34.65	40.47	45.45	41.41	51.79	40.70	29.74
Hear.	47.90	52.66	54.55	55.72	53.74	61.24	33.50
Arrh.	68.91	70.46	74.41	71.13	75.92	72.12	33.05
Park.	74.93	85.09	75.06	74.40	82.87	62.94	65.35

Table A48 (continued)

AUPRC: detectors 8–14

Dataset	LDGOD	ICL	DeepSVDD	DIF	SLAD	RCA	NeuTraL
PenD.	4.74	0.77±0.37	0.39±0.16	0.76±0.15	2.82±1.37	0.20±0.04	0.82±0.29
Sati.	40.23	0.67±0.06	1.24±0.25	93.36±2.43	23.06±11.40	93.97±0.44	3.85±2.36
Shut.	33.15	7.88±8.54	3.98±2.37	33.60±2.03	48.98±25.64	10.12±1.50	25.02±7.00
WBC	63.12	38.58±16.25	9.46±3.87	36.65±5.03	59.46±5.79	48.32±2.10	9.66±1.41
Thyr.	32.61	5.77±3.82	36.07±2.91	46.23±2.43	9.66±5.74	34.53±1.17	27.00±8.34
WDBC	53.32	21.07±12.85	6.81±4.28	36.85±4.55	6.44±4.79	45.42±4.25	11.34±1.51
Optd.	2.16	5.32±1.30	3.06±1.32	2.93±0.21	4.21±0.71	2.63±0.20	2.96±0.83
Wave.	11.19	2.83±0.46	2.91±0.27	7.36±0.70	5.30±1.03	4.43±0.41	3.65±0.84
Musk	34.02	6.44±2.66	10.68±9.12	99.48±0.67	49.31±16.06	64.58±3.71	39.83±17.81
Vowe.	55.96	14.82±7.04	16.82±5.19	30.03±4.91	33.87±11.00	11.56±1.71	12.75±4.85
Lymp.	66.36	11.18±8.45	26.26±3.17	30.40±1.94	63.73±5.19	62.91±0.98	33.86±7.26
Glass	13.14	5.08±3.32	11.44±5.21	19.41±3.62	16.45±9.47	5.66±0.75	13.68±3.40
Wilt	6.38	8.84±1.65	6.48±1.23	3.87±0.06	11.27±3.37	4.10±0.13	11.49±7.20
Lett.	30.02	6.85±0.83	10.07±1.78	13.78±0.90	38.68±2.94	6.96±0.60	18.58±2.48
Annt.	13.27	7.57±1.81	12.74±7.51	10.81±0.28	8.28±1.85	9.80±0.15	8.71±1.05
Wine	19.70	11.72±4.57	7.11±1.39	12.01±1.05	7.96±1.73	25.70±4.37	5.59±0.74
Stam.	27.51	6.92±1.70	17.96±5.11	27.36±0.78	9.02±2.76	19.91±2.09	21.80±2.10
Mnist	39.76	19.39±2.54	20.99±8.67	37.99±0.82	41.26±3.24	35.82±0.89	22.36±4.08
Page.	45.15	10.96±3.43	26.25±10.28	60.06±1.31	25.25±6.14	46.24±1.14	45.70±10.72
Vert.	8.99	11.75±0.91	11.66±1.97	9.14±0.22	10.68±1.07	8.99±0.32	11.19±0.64
Card.	30.99	17.97±2.07	28.84±4.38	36.49±0.91	16.90±0.77	42.90±0.98	33.45±5.21
WPBC	22.80	24.56±3.08	20.38±1.42	22.03±0.49	24.26±1.61	23.95±0.99	22.37±1.35
Sate.	54.53	35.53±4.07	39.75±4.48	62.46±2.42	47.56±2.38	44.03±2.96	43.53±2.29
Pima	51.69	33.29±4.03	35.94±4.95	50.60±0.74	35.39±2.39	51.55±1.33	41.95±1.53
Brea.	92.48	44.47±11.10	38.30±4.57	88.78±0.63	74.45±10.55	95.81±0.39	52.59±2.08
Iono.	91.64	26.28±2.96	39.03±4.75	87.85±0.39	71.52±4.59	66.87±1.18	92.01±0.65
Spam.	40.30	40.90±5.54	35.53±4.03	40.93±0.36	34.11±1.38	41.13±0.32	41.11±3.05
Hear.	55.46	48.54±6.24	43.27±2.98	54.45±1.33	51.36±4.24	59.82±2.15	43.94±2.76
Arrh.	70.84	60.25±6.46	57.43±3.63	70.67±0.22	53.11±5.10	47.66±2.88	63.85±1.93
Park.	82.06	77.36±5.37	79.43±3.97	78.36±1.18	80.79±2.24	80.08±1.35	72.61±2.49

Table A49: Per-dataset anomaly-score statistics using one specified seed per dataset and reported oracle precision. AE seeds are selected for the largest oracle AUROC gain among ten seeds per dataset.

(a) AE: Original

Dataset	Seed	AUROC	Normal mean	Normal SD	Anomaly mean	Anomaly SD
PenD.	0	27.08	48.52	13.80	39.82	7.42
Sati.	2	95.20	21.51	11.37	56.14	17.93
Shut.	9	19.26	3.21	3.57	1.25	1.66
WBC	5	89.71	3.98	2.66	25.31	27.80
Thyr.	0	16.23	16.91	6.66	11.03	12.91
WDBC	9	93.42	8.40	8.52	39.20	23.66
Optd.	6	25.89	2.79	3.93	1.50	0.81
Wave.	2	34.32	48.20	14.16	40.28	13.83
Musk	7	74.37	29.17	11.45	46.21	20.93
Vowe.	8	31.90	49.27	16.06	38.87	15.26
Lymp.	3	63.09	40.79	15.41	43.23	12.09
Glass	1	17.62	24.48	10.59	15.31	7.73
Wilt	1	31.13	5.65	2.64	4.63	0.85
Lett.	5	47.17	25.09	9.48	23.95	10.01
Annt.	0	39.11	0.50	1.32	0.45	0.74
Wine	9	63.78	37.28	17.92	42.30	7.70
Stam.	8	28.58	14.43	8.13	11.81	18.04
Mnist	0	58.93	1.21	2.71	2.87	7.49
Page.	0	35.39	17.51	0.76	17.98	10.20
Vert.	4	35.10	10.22	9.04	6.25	3.07
Card.	5	48.99	13.93	7.85	15.92	13.83
WPBC	3	49.85	24.56	16.73	22.65	11.13
Sate.	6	45.24	36.89	21.71	32.59	19.31
Pima	9	68.96	21.63	10.36	28.53	11.99
Brea.	4	96.49	5.33	2.65	30.45	19.79
Iono.	5	50.36	29.96	11.00	33.09	22.59
Spam.	1	55.01	1.50	3.20	1.40	3.61
Hear.	4	68.14	25.46	13.15	34.43	16.24
Arrh.	5	62.90	13.25	6.56	19.37	14.34
Park.	8	53.87	9.26	5.71	12.18	13.65
AVG	-	50.90	19.70	8.97	23.30	12.22

(b) AE: LPR

Dataset	d	AUROC	Normal mean	Normal SD	Anomaly mean	Anomaly SD
PenD.	0	66.78	50.23	16.33	58.86	11.79
Sati.	4	95.50	21.09	11.13	56.15	17.98
Shut.	0	86.93	3.76	3.42	7.73	4.51
WBC	0	98.65	1.98	3.61	33.27	25.92
Thyr.	0	51.40	16.62	7.21	21.09	19.87
WDBC	0	97.68	9.84	7.05	53.10	27.42
Optd.	0	59.10	4.93	4.20	4.97	1.33
Wave.	0	51.22	45.22	14.36	45.72	13.00
Musk	3	82.71	25.84	10.06	45.05	18.51
Vowe.	0	90.15	45.32	15.20	71.96	14.17
Lymp.	3	69.89	40.37	15.48	43.95	12.61
Glass	0	56.59	54.69	10.43	55.48	9.65
Wilt	0	54.45	47.86	8.70	49.47	5.76
Lett.	1	56.40	34.54	13.58	37.16	13.49
Annt.	1	59.63	7.82	1.56	8.22	1.39
Wine	0	95.80	36.93	14.91	70.23	10.79
Stam.	0	66.81	25.29	10.96	31.58	11.99
Mnist	2	83.83	2.34	2.90	4.70	7.36
Page.	0	70.92	0.84	0.58	2.68	6.55
Vert.	1	58.68	12.91	9.12	13.35	4.78
Card.	0	60.06	22.58	10.88	27.13	13.24
WPBC	0	56.47	28.11	16.07	29.89	13.14
Sate.	3	46.87	33.84	19.76	31.48	19.30
Pima	0	76.08	26.53	11.08	38.04	12.80
Brea.	0	99.53	2.57	3.70	39.62	18.50
Iono.	3	50.55	30.34	10.70	33.53	22.26
Spam.	0	60.31	1.85	3.52	1.92	3.65
Hear.	0	85.21	29.70	15.01	53.34	17.26
Arrh.	5	66.56	11.52	6.41	18.70	14.47
Park.	0	79.08	5.68	2.19	14.26	14.62
AVG	-	71.13	22.70	9.34	33.42	12.94

(c) AE: Score differences

Dataset	Original gap	LPR gap	Normal change	Anomaly change
PenD.	-8.70	8.62	1.71	19.04
Sati.	34.63	35.07	-0.42	0.01
Shut.	-1.96	3.97	0.55	6.48
WBC	21.33	31.30	-2.00	7.96
Thyr.	-5.88	4.47	-0.29	10.06
WDBC	30.80	43.27	1.43	13.91
Optd.	-1.29	0.04	2.14	3.47
Wave.	-7.92	0.50	-2.98	5.44
Musk	17.03	19.22	-3.34	-1.15
Vowe.	-10.40	26.65	-3.95	33.09
Lymp.	2.44	3.57	-0.41	0.72
Glass	-9.17	0.79	30.20	40.16
Wilt	-1.02	1.60	42.21	44.83
Lett.	-1.14	2.61	9.46	13.21
Annt.	-0.06	0.40	7.31	7.77
Wine	5.02	33.31	-0.35	27.93
Stam.	-2.62	6.29	10.87	19.77
Mnist	1.65	2.35	1.13	1.83
Page.	0.47	1.84	-16.66	-15.29
Vert.	-3.98	0.44	2.68	7.10
Card.	2.00	4.54	8.66	11.20
WPBC	-1.92	1.78	3.54	7.24
Sate.	-4.29	-2.36	-3.05	-1.12
Pima	6.90	11.51	4.90	9.51
Brea.	25.12	37.05	-2.76	9.17
Iono.	3.12	3.19	0.38	0.45
Spam.	-0.10	0.07	0.35	0.52
Hear.	8.97	23.64	4.23	18.91
Arrh.	6.12	7.18	-1.73	-0.68
Park.	2.92	8.59	-3.58	2.09
AVG	3.60	10.72	3.01	10.12

Table A49 (continued): PAE. SD is within the normal or anomaly sample group under the listed seed.

(d) PAE: Original

Dataset	Seed	AUROC	Normal mean	Normal SD	Anomaly mean	Anomaly SD
PenDigits	4	87.63	17.11	7.35	24.97	4.96
Satimage	9	99.92	19.49	12.10	89.44	6.02
Shuttle	0	95.64	1.29	3.85	13.60	19.32
WBC	6	98.45	1.11	2.91	28.88	26.82
Thyroid	2	94.63	0.92	1.99	9.84	18.72
WDBC	8	90.31	21.58	16.21	49.28	13.39
Optdigits	9	38.38	12.55	9.00	9.52	3.99
Waveform	4	50.34	43.35	13.53	43.69	14.13
Musk	2	99.98	25.14	11.73	77.04	7.74
Vowels	0	63.48	33.86	13.51	42.04	18.72
Lymphography	5	93.72	8.91	11.76	62.69	34.40
Glass	4	81.63	15.63	17.85	33.96	21.77
Wilt	9	32.30	0.40	1.84	0.15	0.13
Letter	5	69.99	26.63	11.82	34.97	11.59
Annthyroid	4	65.89	8.73	12.91	12.67	13.89
Wine	2	2.10	31.24	11.94	6.94	5.10
Stamps	9	91.58	10.86	10.76	29.38	16.33
Mnist	6	85.79	10.95	6.97	25.15	16.32
PageBlocks	8	90.41	2.70	4.68	15.53	12.78
Vertebral	1	55.87	10.38	7.23	10.26	1.82
Cardiotocography	7	45.52	25.03	15.67	27.14	25.60
WPBC	6	46.27	34.00	19.99	31.06	19.64
Satellite	3	82.35	16.96	9.46	42.93	25.07
Pima	5	58.83	11.47	8.12	14.51	11.21
Breastw	0	95.71	4.73	2.35	28.05	19.66
Ionosphere	2	98.56	14.45	10.96	62.45	17.20
SpamBase	5	48.27	24.12	15.02	22.92	12.09
HeartDisease	0	61.24	17.89	12.28	22.81	15.03
Arrhythmia	5	71.33	5.04	5.81	13.14	17.48
Parkinson	2	69.03	15.99	10.01	25.98	17.35
AVG	–	72.17	15.75	9.99	30.37	14.94

(e) PAE: LPR

Dataset	Seed	*d*	AUROC	Normal mean	Normal SD	Anomaly mean	Anomaly SD
PenDigits	4	3	89.97	12.72	5.99	22.24	6.09
Satimage	9	4	99.92	18.96	11.97	86.96	6.85
Shuttle	0	4	95.62	1.28	3.64	13.88	19.87
WBC	6	3	99.08	16.94	22.66	95.49	5.21
Thyroid	2	5	94.63	0.92	1.99	9.84	18.72
WDBC	8	1	97.87	10.25	6.24	51.62	26.08
Optdigits	9	1	87.32	7.95	3.85	11.34	1.52
Waveform	4	3	85.13	40.09	11.25	56.91	11.61
Musk	2	3	100.00	18.31	7.82	72.43	9.71
Vowels	0	0	90.15	45.32	15.20	71.96	14.17
Lymphography	5	3	95.83	9.18	7.29	51.34	28.75
Glass	4	4	81.46	15.71	17.94	34.34	22.83
Wilt	9	1	70.15	4.34	2.97	4.69	0.76
Letter	5	4	84.32	28.91	12.20	47.77	14.75
Annthyroid	4	5	65.97	8.73	12.91	12.69	13.88
Wine	2	2	98.57	27.93	14.83	78.19	13.21
Stamps	9	4	91.62	10.94	10.84	29.63	16.34
Mnist	6	3	90.08	6.54	4.96	17.54	16.71
PageBlocks	8	3	93.99	0.77	2.01	5.08	7.44
Vertebral	1	2	78.37	38.21	14.76	51.42	10.44
Cardiotocography	7	2	78.94	18.28	7.98	27.55	12.17
WPBC	6	2	59.22	26.76	16.98	30.84	16.00
Satellite	3	4	81.92	16.04	8.91	41.50	25.12
Pima	5	2	81.21	41.16	14.59	59.17	15.21
Breastw	0	0	99.53	2.57	3.70	39.62	18.50
Ionosphere	2	4	98.56	15.06	11.32	64.09	17.40
SpamBase	5	2	72.56	4.18	3.37	5.56	3.76
HeartDisease	0	0	85.21	29.70	15.01	53.34	17.26
Arrhythmia	5	4	77.51	19.45	9.93	35.18	19.58
Parkinson	2	2	85.36	5.35	2.16	15.64	14.67
AVG	–	–	87.00	16.75	9.51	39.93	14.15

(f) PAE: Score differences

Dataset	Original gap	LPR gap	Normal change	Anomaly change
PenDigits	7.86	9.52	-4.39	-2.73
Satimage	69.96	68.00	-0.52	-2.48
Shuttle	12.32	12.60	-0.00	0.28
WBC	27.76	78.56	15.82	66.62
Thyroid	8.92	8.92	0.00	0.00
WDBC	27.70	41.36	-11.33	2.33
Optdigits	-3.02	3.40	-4.60	1.82
Waveform	0.34	16.82	-3.26	13.22
Musk	51.89	54.11	-6.83	-4.61
Vowels	8.18	26.65	11.46	29.92
Lymphography	53.79	42.16	0.28	-11.35
Glass	18.33	18.63	0.08	0.38
Wilt	-0.26	0.35	3.94	4.54
Letter	8.34	18.86	2.28	12.80
Annthyroid	3.94	3.96	0.00	0.02
Wine	-24.29	50.26	-3.31	71.24
Stamps	18.51	18.70	0.07	0.26
Mnist	14.20	11.00	-4.41	-7.61
PageBlocks	12.83	4.32	-1.93	-10.44
Vertebral	-0.12	13.21	27.83	41.16
Cardiotocography	2.11	9.27	-6.75	0.42
WPBC	-2.94	4.08	-7.24	-0.22
Satellite	25.97	25.46	-0.92	-1.44
Pima	3.04	18.02	29.68	44.66
Breastw	23.32	37.05	-2.16	11.57
Ionosphere	48.00	49.03	0.61	1.64
SpamBase	-1.20	1.38	-19.95	-17.37
HeartDisease	4.92	23.64	11.81	30.53
Arrhythmia	8.10	15.73	14.41	22.04
Parkinson	9.99	10.29	-10.64	-10.34
AVG	14.62	23.18	1.00	9.56

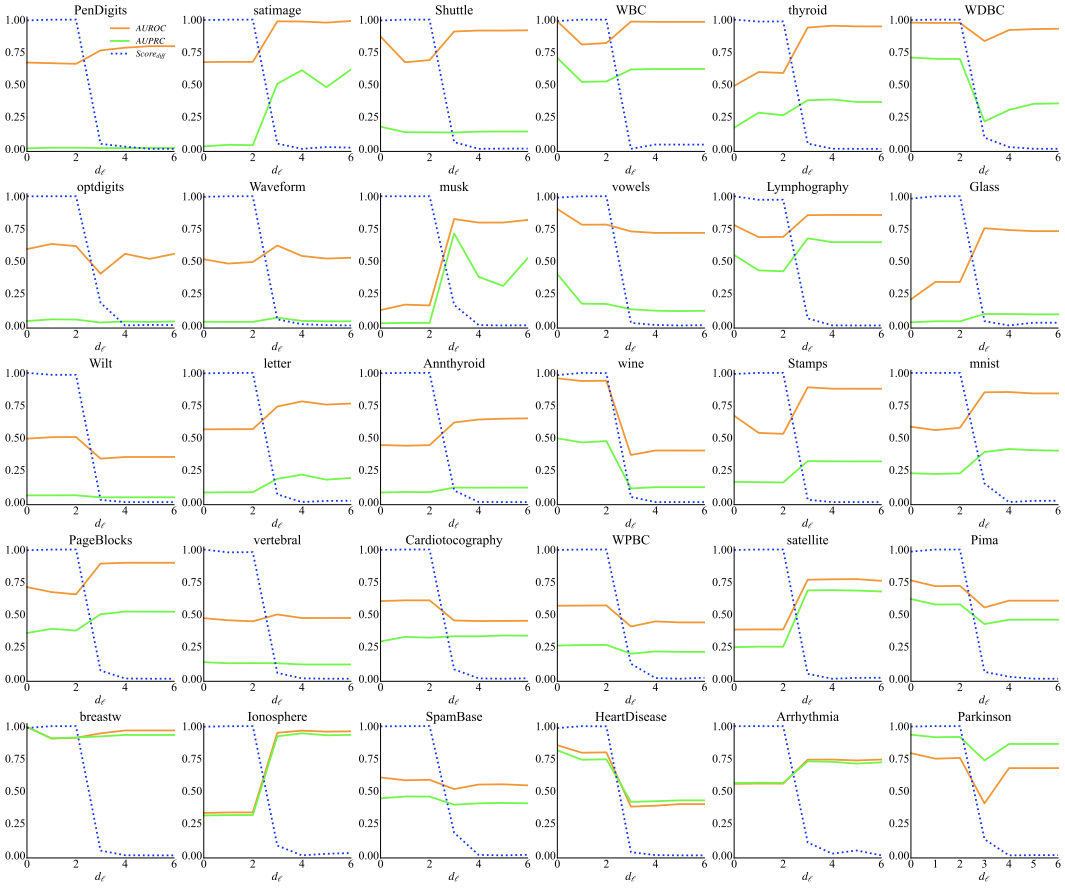


Figure A1: A potential approach for selecting the optimal d_ℓ is to identify the turning point (indicated by the grey dashed line) in the change of mean anomaly scores, relative to those produced by the original model (i.e., with $d_\ell = 6$). `Scorediff` denotes this mean-score change.

D.2.5 LPR's Parameter Analysis

Fig. A1 complements Fig. 2 by illustrating a potential method for selecting the optimal d_ℓ for each dataset, using the PAE detector as an example.

D.3 Per-dataset results for regularization and quantization methods

Table A50: Dropout per-dataset results under seed-wise oracle selection (%); SD is over ten seeds.

Dataset	AUROC mean	AUROC SD	AUPRC mean	AUPRC SD
PenDigits	62.45	15.93	0.34	0.21
Satimage	99.03	0.37	95.80	0.64
Shuttle	76.90	21.59	13.94	11.13
WBC	97.54	2.80	66.90	6.62
Thyroid	68.90	26.49	26.76	20.04
WDBC	94.79	1.24	56.57	9.70
Optdigits	54.47	16.73	3.26	1.05
Waveform	65.55	12.09	4.79	1.32
Musk	100.00	0.00	100.00	0.01
Vowels	69.44	14.15	14.30	16.58
Lymphography	66.71	25.44	46.12	28.17
Glass	44.03	19.81	4.21	1.75
Wilt	39.49	7.45	4.03	0.47
Letter	53.76	3.12	7.22	0.89
Annthyroid	52.50	9.49	9.59	2.32
Wine	87.87	8.41	33.57	15.76
Stamps	63.02	17.15	17.25	8.01
Mnist	75.90	3.73	32.12	3.45
PageBlocks	50.96	13.68	29.53	11.98
Vertebral	33.16	8.06	8.83	0.93
Cardiotocography	67.61	11.87	40.16	12.08
WPBC	53.83	3.10	24.78	2.53
Satellite	56.03	3.28	56.35	2.64
Pima	73.01	4.12	57.30	4.37
Breastw	98.65	0.65	97.81	0.92
Ionosphere	71.39	5.38	67.59	3.46
SpamBase	59.80	1.13	43.91	0.87
HeartDisease	77.91	7.34	71.27	8.31
Arrhythmia	72.36	1.94	70.29	1.23
Parkinson	64.97	9.67	86.65	5.09

Table A51: WeightDecay per-dataset results under seed-wise oracle selection (%); SD is over ten seeds.

Dataset	AUROC mean	AUROC SD	AUPRC mean	AUPRC SD
PenDigits	58.66	16.40	0.29	0.20
Satimage	94.04	3.68	68.68	19.14
Shuttle	73.76	23.49	12.99	10.51
WBC	97.56	2.63	66.77	6.41
Thyroid	66.82	25.59	25.21	19.63
WDBC	95.64	1.36	59.46	11.25
Optdigits	53.68	15.63	3.25	1.24
Waveform	56.49	14.47	3.84	1.48
Musk	82.11	15.20	45.11	23.59
Vowels	64.70	15.71	12.00	14.40
Lymphography	66.71	25.44	46.12	28.17
Glass	43.79	20.24	4.23	1.75
Wilt	39.36	7.24	4.02	0.45
Letter	53.03	3.79	7.29	1.30
Annthyroid	48.53	6.97	8.45	1.40
Wine	86.34	9.34	32.36	17.68
Stamps	62.00	16.96	16.61	7.71
Mnist	69.40	5.06	28.40	2.35
PageBlocks	50.16	13.94	28.95	12.15
Vertebral	31.78	7.55	8.67	0.89
Cardiotocography	66.29	10.36	38.14	8.85
WPBC	54.45	2.07	25.07	1.74
Satellite	49.41	3.06	43.12	8.20
Pima	73.51	3.79	57.86	4.09
Breastw	98.51	0.93	97.62	1.27
Ionosphere	51.52	4.68	51.31	4.82
SpamBase	57.94	1.72	42.67	1.09
HeartDisease	78.65	5.22	72.15	6.09
Arrhythmia	59.74	3.84	60.83	3.83
Parkinson	65.39	8.78	87.10	4.24

Table A52: Noise per-dataset results under seed-wise oracle selection (%); SD is over ten seeds.

Dataset	AUROC mean	AUROC SD	AUPRC mean	AUPRC SD
PenDigits	58.77	16.43	0.29	0.20
Satimage	94.89	2.73	72.28	17.49
Shuttle	74.18	23.43	12.96	10.65
WBC	97.68	2.33	67.71	4.95
Thyroid	66.83	25.59	25.29	19.78
WDBC	95.82	1.34	60.17	10.94
Optdigits	56.17	14.85	3.40	1.20
Waveform	57.19	14.56	3.93	1.49
Musk	94.09	5.25	65.60	19.06
Vowels	65.72	15.41	12.13	14.33
Lymphography	66.76	25.49	46.56	28.52
Glass	44.08	20.33	4.26	1.78
Wilt	39.70	7.50	4.05	0.48
Letter	52.98	3.65	7.33	1.30
Annthyroid	50.77	7.56	8.99	1.64
Wine	86.39	9.41	33.08	18.88
Stamps	62.02	16.97	16.91	8.04
Mnist	74.21	5.44	31.19	3.48
PageBlocks	52.96	12.51	30.65	11.45
Vertebral	31.81	7.57	8.67	0.89
Cardiotocography	67.41	10.79	39.08	9.38
WPBC	55.26	2.11	25.56	1.69
Satellite	49.77	2.90	44.10	6.86
Pima	73.70	3.85	58.03	4.15
Breastw	98.61	0.75	97.73	1.13
Ionosphere	53.24	4.10	52.77	4.53
SpamBase	58.41	1.60	42.97	1.07
HeartDisease	78.81	5.40	72.27	6.24
Arrhythmia	61.59	3.83	62.14	3.76
Parkinson	67.01	8.78	87.83	4.26

Table A53: PTQ per-dataset results under seed-wise oracle selection (%); SD is over ten seeds.

Dataset	AUROC mean	AUROC SD	AUPRC mean	AUPRC SD
PenDigits	58.66	16.45	0.29	0.20
Satimage	94.04	3.69	68.69	19.12
Shuttle	73.95	23.32	13.03	10.48
WBC	97.56	2.64	66.80	6.43
Thyroid	66.72	25.58	25.16	19.63
WDBC	95.65	1.36	59.46	11.25
Optdigits	53.59	15.45	3.23	1.22
Waveform	56.52	14.47	3.85	1.49
Musk	82.16	15.21	45.25	23.62
Vowels	64.70	15.74	12.02	14.44
Lymphography	66.68	25.45	46.11	28.17
Glass	43.78	20.25	4.23	1.75
Wilt	39.34	7.16	4.01	0.44
Letter	53.03	3.79	7.29	1.29
Annthyroid	48.60	7.00	8.46	1.41
Wine	86.30	9.37	32.34	17.69
Stamps	62.02	16.96	16.61	7.74
Mnist	69.33	5.08	28.36	2.34
PageBlocks	50.07	13.94	28.91	12.18
Vertebral	31.79	7.57	8.67	0.90
Cardiotocography	66.27	10.39	38.14	8.89
WPBC	54.45	2.09	25.07	1.75
Satellite	49.41	3.05	43.13	8.18
Pima	73.52	3.79	57.87	4.10
Breastw	98.52	0.92	97.63	1.27
Ionosphere	51.51	4.69	51.29	4.82
SpamBase	57.95	1.72	42.67	1.08
HeartDisease	78.65	5.23	72.15	6.11
Arrhythmia	59.74	3.84	60.82	3.83
Parkinson	65.38	8.80	87.09	4.25

Table A54: QAT per-dataset results under seed-wise oracle selection (%); SD is over ten seeds.

Dataset	AUROC mean	AUROC SD	AUPRC mean	AUPRC SD
PenDigits	57.87	16.39	0.29	0.20
Satimage	92.53	6.48	64.71	25.98
Shuttle	73.50	23.73	13.02	10.49
WBC	97.55	2.65	66.72	6.50
Thyroid	66.83	25.56	25.20	19.62
WDBC	95.61	1.34	59.38	10.95
Optdigits	53.82	15.77	3.27	1.26
Waveform	56.72	14.44	3.85	1.49
Musk	80.82	15.81	40.01	22.78
Vowels	64.70	15.73	12.03	14.44
Lymphography	66.81	25.43	46.12	28.16
Glass	43.77	20.26	4.23	1.75
Wilt	39.33	7.14	4.01	0.44
Letter	53.08	3.82	7.30	1.31
Annthyroid	48.17	7.37	8.39	1.45
Wine	86.32	9.30	32.37	17.83
Stamps	62.00	16.94	16.64	7.80
Mnist	69.35	4.77	28.33	2.21
PageBlocks	50.02	14.05	28.84	12.27
Vertebral	31.79	7.58	8.67	0.90
Cardiotocography	66.66	10.80	38.51	9.38
WPBC	54.38	2.04	25.03	1.68
Satellite	49.08	3.50	42.36	8.98
Pima	73.43	3.86	57.77	4.15
Breastw	98.57	0.81	97.67	1.23
Ionosphere	51.39	4.87	51.30	4.82
SpamBase	57.85	1.64	42.63	1.04
HeartDisease	78.39	5.80	71.97	6.50
Arrhythmia	59.77	4.05	60.91	4.03
Parkinson	65.31	8.86	87.06	4.27

Table A55: LPR per-dataset results under seed-wise oracle selection (%); SD is over ten seeds.

Dataset	AUROC mean	AUROC SD	AUPRC mean	AUPRC SD
PenDigits	70.74	6.15	0.43	0.16
Satimage	94.09	3.70	68.99	19.24
Shuttle	90.87	4.44	22.41	8.82
WBC	98.68	0.08	70.93	1.33
Thyroid	79.77	18.91	38.44	27.26
WDBC	97.74	0.15	71.30	1.48
Optdigits	65.87	9.18	4.39	1.48
Waveform	62.33	9.11	4.20	1.19
Musk	83.43	15.12	46.90	23.19
Vowels	90.62	1.40	42.78	6.76
Lymphography	67.65	25.55	47.39	28.77
Glass	50.16	16.46	4.78	1.69
Wilt	45.53	8.72	4.55	0.84
Letter	56.71	0.56	7.92	0.93
Annthyroid	60.53	8.27	13.83	5.78
Wine	96.05	0.54	52.01	5.48
Stamps	73.01	6.60	20.00	6.68
Mnist	79.63	6.32	37.54	8.69
PageBlocks	72.40	4.44	38.87	7.05
Vertebral	39.10	9.13	9.88	1.94
Cardiotocography	68.83	7.93	39.34	8.42
WPBC	56.60	0.30	26.22	0.67
Satellite	49.72	2.92	43.57	7.77
Pima	76.86	1.23	62.26	0.88
Breastw	99.53	0.00	99.11	0.00
Ionosphere	51.55	4.67	51.42	4.85
SpamBase	60.32	0.04	44.15	0.11
HeartDisease	85.47	0.52	81.42	0.39
Arrhythmia	60.77	3.84	61.57	3.76
Parkinson	79.98	1.85	93.62	0.51

D.4 Precision associations and detector–dataset improvement rates

For each model and dataset, the AUROC-optimal precision is selected after averaging the ten seeds, with exact ties assigned to the smaller d. Table A56 reports Spearman rank correlations (ρ) between this precision and sample count, feature dimensionality, and anomaly count. Each correlation uses 30 datasets and is computed separately for each model. The same constant-score zero-penalty convention is used as in the other analyses.

Table A56: Spearman correlations between AUROC-optimal precision and dataset characteristics under mean-first oracle selection.

Detector	Sample count	Feature dimensionality	Anomaly count
AE	0.153	0.237	0.133
MCM	0.157	-0.182	-0.135
DTE	0.443	-0.175	0.009
VAE	0.248	0.274	0.212
β-VAE	0.232	0.280	0.215
PAE	0.458	0.129	0.014
U-DRL	0.179	-0.037	0.028
S-DRL	-0.095	0.015	-0.060
FEAWAD	0.023	0.125	0.195
MLP	0.063	0.113	0.009

The strongest positive sample-count associations occur for PAE ($\rho = 0.458$) and DTE ($\rho = 0.443$). Associations with feature dimensionality and anomaly count are weaker and vary in direction across models. These results describe model-dependent relationships between dataset characteristics and the selected precision.

For each detector–dataset pair and each metric, the gain is the mean-first oracle score minus the corresponding Original baseline mean over ten seeds. Table A57 reports the number and percentage of pairs with a positive gain and with a gain greater than 0.1 percentage points. The full benchmark contains 300 pairs; excluding the seven datasets with fewer than 30 anomalies leaves 230 pairs. Counts are computed before rounding the reported means.

On the 23-dataset subset, weighting each dataset's gain by its sample count and averaging equally across the ten detectors gives gains of 4.45 AUROC and 4.37 AUPRC percentage points.

Table A57: Detector–dataset improvement counts and percentages under mean-first oracle selection. Gain thresholds are in percentage points.

	AUROC gain		AUPRC gain	
Dataset scope	> 0	> 0.1	> 0	> 0.1
All 30 datasets	261/300 (87.0%)	232/300 (77.3%)	259/300 (86.3%)	229/300 (76.3%)
23 datasets	206/230 (89.6%)	178/230 (77.4%)	200/230 (87.0%)	175/230 (76.1%)

NeurIPS Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: The abstract identifies the empirical scope as tabular anomaly detection and states that the headline improvements use test-set precision selection. Section 5.1 distinguishes seed-wise oracle, mean-first oracle, fixed precision, and leave-one-dataset-out evaluation; Table 1 reports the corresponding comparisons.

   Guidelines:

   - The answer [N/A] means that the abstract and introduction do not include the claims made in the paper.
   - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A [No] or [N/A] answer to this question will not be perceived well by the reviewers.
   - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
   - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [Yes]

   Justification: Section 4.5 and Appendix B.3 discuss precision-sensitive normal subpopulations, false positives, and conditions under which LPR may not improve detection. Section 5.7 discusses precision selection without labels, and Appendix C.6 describes the scope of the bottleneck ablation.

   Guidelines:

   - The answer [N/A] means that the paper has no limitation while the answer [No] means that the paper has limitations, but those are not discussed in the paper.
   - The authors are encouraged to create a separate "Limitations" section in their paper.
   - The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
   - The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
   - The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
   - The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
   - If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
   - While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory assumptions and proofs**

   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

   Answer: [Yes]

   Justification: Section 4 states the parameter-Lipschitz assumption and residual bounds used in Proposition 1 and provides its proof sketch. Lemma 1 states the nested-subspace and orthogonal-projection assumptions and includes a proof. The constructive example and bias–variance discussion are identified as conditional explanations.

   Guidelines:

   - The answer [N/A] means that the paper does not include theoretical results.
   - All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
   - All assumptions should be clearly stated or referenced in the statement of any theorems.
   - The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
   - Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
   - Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental result reproducibility**

   Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

   Answer: [Yes]

   Justification: The paper provides the LPR update rule, pseudocode, benchmark descriptions, selection protocols, and per-dataset results.

   Guidelines:

   - The answer [N/A] means that the paper does not include experiments.
   - If the paper includes experiments, a [No] answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
   - If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
   - Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general. releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
   - While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
     (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
     (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
     (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).

(d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

   Answer: [No]

   Justification: The paper cites public benchmark sources and the original baseline methods and includes illustrative LPR code. A complete training and evaluation code release with environment specifications and end-to-end reproduction instructions is not provided.

   Guidelines:

   - The answer [N/A] means that paper does not include experiments requiring code.
   - Please see the NeurIPS code and data submission guidelines (`https://neurips.cc/public/guides/CodeSubmissionPolicy`) for more details.
   - While we encourage the release of code and data, we understand that this might not be possible, so [No] is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
   - The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (`https://neurips.cc/public/guides/CodeSubmissionPolicy`) for more details.
   - The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
   - The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
   - At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
   - Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental setting/details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer) necessary to understand the results?

   Answer: [Yes]

   Justification: Appendix B.4 describes preprocessing, supervision settings, seeds, and data splits, while Appendix C.3 and Table A10 provide regularization and quantization settings.

   Guidelines:

   - The answer [N/A] means that the paper does not include experiments.
   - The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
   - The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment statistical significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [Yes]

   Justification: The paper reports per-dataset standard deviations over ten training seeds and defines pooled dispersions for several aggregate comparisons. No confidence intervals or significance tests for paired gains are reported.

Guidelines:

- The answer [N/A] means that the paper does not include experiments.
- The authors should answer [Yes] if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g., negative error rates).
- If error bars are reported in tables or plots, the authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [No]

   Justification: Appendix C.7 describes the projection complexity and the cost of evaluating multiple precision candidates. The paper does not provide a complete account of hardware, memory requirements, per-run execution times, or total experimental compute.

   Guidelines:

   - The answer [N/A] means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
   - The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
   - The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code of ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

   Answer: [Yes]

   Justification: The study evaluates an anomaly-detection method on existing public benchmarks and does not recruit participants or conduct user studies. The authors affirm that the research was conducted in accordance with the NeurIPS Code of Ethics.

   Guidelines:

   - The answer [N/A] means that the authors have not reviewed the NeurIPS Code of Ethics.
   - If the authors answer [No], they should explain the special circumstances that require a deviation from the Code of Ethics.
   - The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [No]

    Justification: The paper focuses on the method and benchmark evaluation. It discusses false positives affecting minority normal patterns, but does not provide a dedicated assessment of positive and negative societal impacts or deployment-specific mitigation measures.

    Guidelines:

    - The answer [N/A] means that there is no societal impact of the work performed.
    - If the authors answer [N/A] or [No], they should explain why their work has no societal impact or why the paper does not address societal impact.
    - Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
    - The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate Deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
    - The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
    - If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

    Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pre-trained language models, image generators, or scraped datasets)?

    Answer: [N/A]

    Justification: The work does not release a new high-risk dataset or pretrained model of the types described in this question. The experiments use existing public anomaly-detection benchmarks.

    Guidelines:

    - The answer [N/A] means that the paper poses no such risks.
    - Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
    - Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
    - We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

    Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [No]

Justification: The paper credits benchmark sources and baseline methods through citations. It does not explicitly list the license names, versions, and terms of use for all datasets and software assets.

Guidelines:

- The answer [N/A] means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [N/A]

Justification: The submission does not release a new dataset, pretrained model, or standalone software package. The illustrative code and experimental tables are included in the paper.

Guidelines:

- The answer [N/A] means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [N/A]

Justification: The study uses existing benchmark datasets and does not involve crowdsourcing, participant recruitment, or new experiments with human subjects.

Guidelines:

- The answer [N/A] means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

    Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

    Answer: [N/A]

    Justification: The study does not recruit participants or conduct new human-subject experiments. This item does not apply to the reported benchmark evaluation.

    Guidelines:

    - The answer [N/A] means that the paper does not involve crowdsourcing nor research with human subjects.
    - Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
    - We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
    - For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

    Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does *not* impact the core methodology, scientific rigor, or originality of the research, declaration is not required.

    Answer: [N/A]

    Justification: LLMs are not used as an important, original, or non-standard component of the proposed method.

    Guidelines:

    - The answer [N/A] means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
    - Please refer to our LLM policy in the NeurIPS handbook for what should or should not be described.